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The Intraday Relationship between Order Flow and Exchange Rates in the Foreign Exchange Market

Navn: Janne-Birthe Mork Strand

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Janne-Birthe Mork Strand

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Supervisor:
Prof. Dagfinn Rime

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Preface

This master thesis is written in part of the Master of Science degree in Business with major in Finance at BI Norwegian Business School. The process was established during spring 2016 with choice of topic, continued with the submission of a Preliminary Report in January 2017, and ended with the final thesis submission September 1st, 2017.

I would like to thank my supervisor Dagfinn Rime for introducing the exciting topic and providing guidance throughout the process.

Abstract

This master thesis examines the relationship between order flow and exchange rate returns for the EUR/NOK, USD/GBP, and USD/ZAR currency pairs. It investigates this relationship on a general level by looking at the explanatory power of order flow using a hybrid model in contrast to a traditional macro model. It continues with investigating how this relationship varies between liquid and less liquid periods, by specifically looking at how it varies throughout the day. The analysis is extended by looking at order flow impact during the world financial crisis and on holidays. The overall results find no distinct pattern in how the liquidity in the market affects order flow´s impact on exchange rates.

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1. Introduction

The foreign exchange (FX) market is the largest financial market in the world with a daily turnover of $5.1 trillion (BIS, 2016). Harvey and Huang (1991) remark several characteristics of the FX market that distinguish it from other financial markets. The trading is primarily over-the-counter, and major traders are foreign exchange brokers and banks. The emergence of electronic trading and globalization have contributed to high volume, twenty-four-hour trading. These features make the market highly liquid, and as a result, the FX market is believed to be the most efficient financial market. These characteristics make the FX market strikingly interesting, and the determination of exchange rates has sparked a lively debate within the academic profession.

The classical models of macroeconomic theory state that exchange rates are determined by a set of macroeconomic variables, such as GDP growth, interest rates, money supply, and inflation among others. The models of uncovered interest rate parity (UIP) and purchasing power parity (PPP) were helpful for explaining exchange rate movements in the long run, but did not provide explanations for short-run movements. Because of such disappointing empirical results a new field of study emerged: the theory of microstructure. This theory assumes that market participants have heterogeneous expectations, and thereby the structure of the market itself, through information, might influence exchange rate determination.

The field of microstructure finance directs attention to new variables, variables that earlier were not taken into consideration. The most important determinant in microstructure models is order flow. Order flow is defined as the net of buyer-initiated and seller-initiated orders, and is thereby a measure of net buying pressure in the market (Evans and Lyons, 1999). The reason for its importance is that order flow conveys information. Several studies have found evidence for a strongly positive correlation between order flow and nominal exchange rates, indicating that price increases with buying pressure. This represents a radical shift from traditional macro-models, which state that actual trades are neither necessary nor sufficient for price movements.

1.1 Research Question

The main objective of this study is to investigate the formation of prices in the foreign exchange market. Main determinants for prices are information and participants' expectations of the future. One approach to interpret how information is implemented in prices is to compare times with large trading volume with times where almost no active trading takes place. This will give insight into whether the processing of information relates to the actual trading going on in the market at that time, and if the trading volume affects participants' actions and expectations. It also gives insight into how the liquidity of the FX market affects prices. Prices in a highly liquid market have a tendency to move gradually and in small increments. In a less liquid market, prices tend to move more abruptly and in larger increments.

Liquidity in the FX market peaks during European and London opening hours, which overlaps with the Asian market in the morning and North American markets in the afternoon. Liquidity drops after the close of European trading. Liquidity is also lower during market holidays, and is weakened by seasonal periods of reduced market interest, as during Christmas and Easter, and in the late summer. One way to investigate how liquidity affects prices is therefore to look at how the relationship between order flow and prices varies throughout the day.

This thesis will investigate determinants of exchange rate movements using high-frequency data over the period 1999 to 2015. It will focus generally on the relationship between price movements and order flow, and specifically how this varies on an intraday level, and how it varies in periods with fluctuating liquidity. The analysis is therefore split into two parts, where the first investigates the relationship on a general level, while the second focuses on how this varies throughout the day. To address these questions, models that include both macroeconomic determinants (interest rate differential and oil price) and a microstructure determinant (order flow) will be estimated. In addition, it will investigate this relationship in the light of several state parameters: volume, bid-ask spread, and volatility. The research question is specified as:

"How does the relationship between order flow and exchange rates vary on an intraday level?"

1.2 Contribution and Motivation

This analysis is important in a general manner because it can contribute to answering some of the deepest and most important issues in finance: how prices are determined. Because of the characteristics of the FX market, determination of exchange rates, which are after all just prices, is even more complex than in other financial markets. In the literature, there is no single theory fully explaining the exchange rate determination. More specifically this study can help to explain the impact of order flow on prices in the FX market, and how this is related to liquidity and other factors like volume, bid-ask spreads etc. This is important to all market participants and other relevant actors making investment decisions and trying to understand the market. The overall motivation for the study is therefore that it hopefully can contribute, if only a tiny bit, to enhance the understanding of unsolved exchange rate puzzles.

The rest of this paper is organised as follows. In section 2 a literature review is provided to give an overview of the field and the theory. Section 3 lays out the methodology that will be used in the analysis. Section 4 describes the data and presents descriptive statistics, correlation and unit root tests. The empirical analysis will be presented in section 5, including results, interpretations and discussions. Section 5.1 examines the explanatory power of order flow on exchange rate returns. How this varies on an intraday level is analysed in section 5.2. In addition, the analysis is extended by evaluating the world financial crisis and holidays. Section 6 concludes.

2. Theory and Literature Review

2.1 Macro Models

The early macro models of floating exchange rates were designed inductively due to the absence of historical experience. These standard models of exchange rates are based on the view that only common knowledge macroeconomic information matters. They are built on macroeconomic variables such as interest rates, GDP growth, price levels, inflation etc. Uncovered interest rate parity (UIP) and purchasing power parity (PPP) state that the exchange rate is supposed to balance the relative price levels and interest rates in two countries, and are well-established models in macroeconomic theory.

In the 1990s, these macro models showed disappointing empirical performance. In research conducted by Hodrick (1988) and Engel (1996), UIP and PPP both failed to hold at short horizons. The PPP model is helpful in explaining long-run exchange rate movements, but provides little explanation for movements in the exchange rate in the short-run. Evans and Lyons (2002) analysed real world data and found that the R^2 of models based on macroeconomic fundamentals rarely exceeds 10%, and forecasts based on them are not better than random walk simulations, they are actually performing worse. These models also fail to predict the direction of the exchange rate change, and are thereby defeated by a simple "no change" framework.

Flood and Rose (1995) contributed to the investigation of determinants of exchange rates when they studied the implications of exchange rate volatility in regimes of fixed and floating rates for typical OECD countries. It is a fact that the volatility of a given exchange rate rises dramatically when a previously fixed exchange rate is floated. But they did not find corresponding variation in macroeconomic volatility, indicating that macroeconomic variables are unable to explain much exchange rate volatility. Their conclusion was thereby that the most critical determinants of exchange rate volatility are not macroeconomic.

2.2 Microstructure

In light of these failures, a microeconomic approach to understand the determination of exchange rates emerged in the 1990s. Researchers proposed that the massive trading volume in the FX market is the reason why the fundamental approach fails. Trading activity has no role relative to macroeconomic variables when determining the exchange rate, thereby the traditional models do not account for trading volume. The microstructure approach was designed deductively, and focuses on how the structure of the market itself might influence exchange rate determination. It assumes that market participants may have asymmetric information concerning the state of the macro economy and differ in their motives for trading currencies, thereby emphasizing that heterogeneous beliefs are essential to determine prices (Evans and Rime, 2016).

French and Roll's paper from 1986 discusses how the volatility of equity returns differs during the day. They found especially that prices are more variable during exchange trading hours than during non-trading hours. Their conclusion was that only 4-12% of the daily variance is caused by mispricing. The main reason for varying volatility is differences in the flow of information during trading and non-trading hours, and most of this information is private.

Jones, Kaul, and Lipson (1994) evaluate the flows of public and private information and their relation to short-run volatility. Here, non-trading periods are defined as periods when exchanges are open, but traders endogenously choose not to trade. They find a substantial proportion of daily stock return volatility to occur without trading, and that public information also might lead to trading. Harris and Raviv (1993) find that public information may be the major determinant of short-run volatility. They also state that even without any private information, and therefore without any information asymmetry, trading can occur due to differences in opinion.

Macroeconomic theory generally assumes that agents are symmetrically heterogeneous, which means they differ, but in the same way. In contrast, traders in the FX market can be categorized into different groups depending on their motivation, their attitude towards risk, and their horizons (Evans and Lyons, 2006). Some agent types do not exhibit the behaviour of agents in the standard models. The microstructure view assumes that heterogeneous beliefs are essential to determine prices.

2.3 Order Flow

Microstructure models direct attention to new variables, with order flow as the most important one. Order flow is the proximate determinant of price in all microstructure models. When considering how order flow itself is determined, information is the key. This can include traditional macro fundamentals, but is not limited to them (Evans and Lyons, 1999).

Order flow and nominal exchange rates are strongly positively correlated. Lyons (1995), Payne (2003), and Naranjo and Nimalendran (2000), among others, have proved that foreign exchange order flow conveys information. Microstructure theory emphasize that different agents may have distinct information concerning the state of the macro economy. Order flow enables market makers to aggregate changes in expectations about the state of the economy. Thereby, order flow affects exchange rates because they contain price-relevant information to market participants.

Evans and Lyons have through several papers reported results that strongly support the microstructure view on exchange rates. Their pioneering paper in 1999 introduced order flow as a determinant, and presented results indicating that the market is indeed aggregating information. They used a model that included interest rates differential and order flow that could explain 60% of the variation in daily exchange rates of DEM/USD. It thereby performs much better than the macroeconomic models. Evans and Lyons (2002) regress the base currency's daily return on order flow and fundamentals. The explanatory power of these regressions is 40-60%, which beats the regressions on fundamentals alone by far. They predict that macroeconomic information influence exchange rates both directly and indirectly via order flow. The common knowledge part of news directly affects the exchange rate by shifting the equilibrium price, while order flow reflects heterogeneous interpretations of these news for the new equilibrium price.

Further, Evans and Rime (2016) report that order flow has significant forecasting power for future depreciation rates over much longer time periods than what has earlier been reported. It was found that order flow's forecasting power arises because flows carry information concerning future risk premium, not information about future interest differentials. They also revealed that the information conveyed by order flows concerning risk premium significantly affected the behaviour of the EUR/NOK exchange rate in several periods around the world financial crisis and European debt crisis.

However, several researchers have found lack of empirical evidence supporting the conclusion that order flow is the significant determinant of exchange rates. Sager and Taylor (2008), using both interdealer and commercially available customer order flow data, found little evidence that order flow could predict exchange rate movements out of sample. In addition, they found a Granger-causal relationship running from exchange rate returns to customer order flow.

Bień-Barkowska (2011) investigates the intradaily relationship between order flow and exchange rates. She finds the intraday foreign exchange rate's sensitivity to changes in order flow to be significantly larger in the morning, afternoon and in periods where there are more premises for informed trading. Breedon and Ranaldo (2013) use a model where returns are a function of current order flow, lagged order flow and lagged returns. They find that the daily pattern order flow, which is a result of different time zones, seems to sufficiently explain the exchange rates' daily seasonality. Lyons (2006) presents two channels through which order flow might affect exchange rates. Order flow might create imbalances in certain dealers' inventory. An inventory-control channel appears when dealers adjust prices to control their inventory fluctuations. An information asymmetry channel emerges when dealers adjust prices in response to customer trades that may contain private information. These two channels are helpful in illustrating why the varying order flow could cause intraday seasonality in exchange rates.

3. Methodology

This section will introduce a basic model that establishes a framework for the empirical analysis in section 5.

As stated in the previous section, a significant discrepancy between the traditional macroeconomic models and the microstructure approach is the importance of trade. In macro models trade has no influence on prices at all, while it in microstructure is the leading determinant for price changes.

The traditional macro models relate exchange rates to monetary variables, output, interest rates, etc.

Public information about macroeconomic fundamentals	→	Price

In general, they are estimated at the form:

$$\Delta p_t = f(\Delta i, \Delta m, \ldots) + \varepsilon_t \qquad \text{(eq. 3.1)}$$

Here, Δp_t is the change in the log nominal exchange rate over the period, typically a month. The independent variables in the function involve the change in nominal and foreign interest rates i, money supply m, and other macroeconomic variables.

Models within the microstructure theory are derived from the optimization problem faced by price setters in the market – the dealers (Evans and Lyons, 1999).

Private information about macroeconomic fundamentals	→	Order flow	→	Price

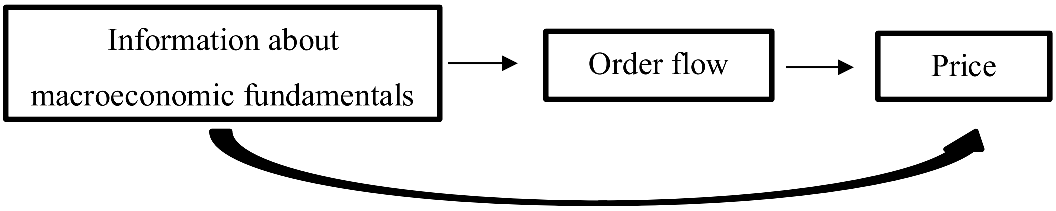
Generally, they take the form:

$$\Delta p_t = g(\Delta x, \Delta I, \ldots) + \varepsilon_t \qquad \text{(eq. 3.2)}$$

Now, Δp_t is the change in the log nominal exchange rate over two transactions. The independent variables are order flow Δx, the change in net dealer positions I, and other micro determinants.

One thing to notice is that the residual in the micro model is the mirror image of the residual in the macro equation. It incorporates price changes due to macro determinants, while the residual in the macro equation incorporates price changes due to micro determinants (Evans and Lyons, 1999).

In this thesis, as in Evans and Lyons (1999, 2002), and several other pioneering papers in the microstructure field, a hybrid model at a daily frequency will be used. These models combine components from both the macro and the micro approach, and establish a framework where macroeconomic information not only impacts prices directly, but also indirectly through order flow. In this framework, order flow reflects the heterogeneity of market participants and transmits this dispersed information to prices.



Hybrid models take the form:

$$\Delta p_t = f(\Delta i, \dots) + g(\Delta x, \dots) + \varepsilon_t \qquad \text{(eq. 3.3)}$$

Different versions of this equation will be exploited, and compared with both a traditional macro model and a simple micro model including only order flow.

To investigate the intradaily relationship, a microstructure model will be used. The hybrid approach is not necessary in this case, since the purpose is to investigate how the relationship between order flow and exchange rate returns varies during the day.

4. Data

4.1 Data Overview

This analysis will focus on the Norwegian krone, the UK sterling and the South African rand, and thereby the following currency pairs will be investigated: EUR/NOK, USD/GBP, and USD/ZAR.

The high-frequency exchange rate data on prices and order flow, including data on volume, bid-ask spread, interest rate differential, volatility, and oil price, are collected from Reuters. The data material comprises two data sets. Data set 1 is daily data on spot and 1-month forward exchange rates, order flow, volume, and bid-ask spreads for the period 1999-2011. It also includes the Brent crude oil price and the volatility indexes VIX, VXYG7, and VXYEM, quoted in USD per barrel ($/barrel) and annualized standard deviation, respectively. Data set 2 comprises daily data from 1999 to 2015 on spot exchange rates, order flow, bid-ask spreads, and volume for different times of the day, one at 07:00 GMT, one at 18:00 GMT, and one at 00:00 GMT. From this, an intradaily data set on exchange rate returns, order flow, bid-ask spreads, and volume is constructed, where each day have three data points.

Although the FX market is open twenty-four hours a day, not much trading occurs between 00:00 GMT and 07:00 GMT, which will be defined as “night”. Between 18:00 GMT and 00:00 GMT is defined as “evening”, and between 07:00 GMT and 18:00 GMT as “day”. When a purchase transaction does not occur precisely at 07, 18, and 00 GMT, the preceding transaction is used. When day t is a Monday, the day t-1 price is the previous Friday`s price.

4.2 Stationarity

To avoid spurious regressions, the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity have been conducted. By looking at the plots of the exchange rates (figure 1), I allow the series to have a mean that is different from zero, but do not include a trend. For the order flow variable, this will be positive some days and negative on others. A long-term mean of zero is therefore expected, thus neither an intercept nor a trend should be included. However, by looking at the plots of order flow for all currency pairs (figure 2), it seems like the mean may be different from zero, especially for the USD/ZAR pair. It is thereby allowed for a mean different from zero also for the order flow series.

The p-values of the unit root tests are presented in table 1. Both tests reveal non-stationarity for the spot exchange rates, the Brent crude oil price, and the volatility indexes VXYG7 and VXYEM. For the rest of the series, the tests show conflicting results: The ADF claims stationarity, while the KPSS suggests rejection of the null hypothesis of stationarity. Therefore, the log spot exchange rate return, and the log of the oil price, bid-ask spread, volume, interest rate differential, and volatility indexes in first differences will be used in the analysis. Table A in the appendix shows that these transformations make the series stationary. For the order flow variable, the issue of non-stationarity is unresolved, but I conduct my analysis assuming stationarity based on the papers by Evans and Lyons (1999, 2002, 2006).

Table 1: Unit Root Tests

Series	**EUR/NOK**		**USD/GBP**		**USD/ZAR**	
Test	**ADF**	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**
Null hypothesis	*Unit root*	*No UR*	*Unit root*	*No UR*	*Unit root*	*No UR*
Spot		**		***		**
Order flow	***	*	***	***	***	***
Bid-ask spread	***	***	***	**	***	***
Volume	***	***	***	***	***	***
Interest rate diff.	***	***	***	***	***	***

Test	**ADF**	**KPSS**
Null hypothesis	*Unit root*	*No unit root*
Oil price		***
VIX	***	***
VXYG7		***
VXYEM		***

Note: Table 1 presents results of the ADF test with the null hypothesis of a unit root, and the KPSS test with the null hypothesis of no unit root. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

4.3 Data set 1

The variables to be analysed in the first part of the thesis include exchange rate returns, order flow, interest rate differential, bid-ask spread, volume, volatility, and oil price. A brief explanation, descriptive statistics, and correlations follows below.

4.3.1 Descriptive Statistics

4.3.1.1 Exchange Rate Returns

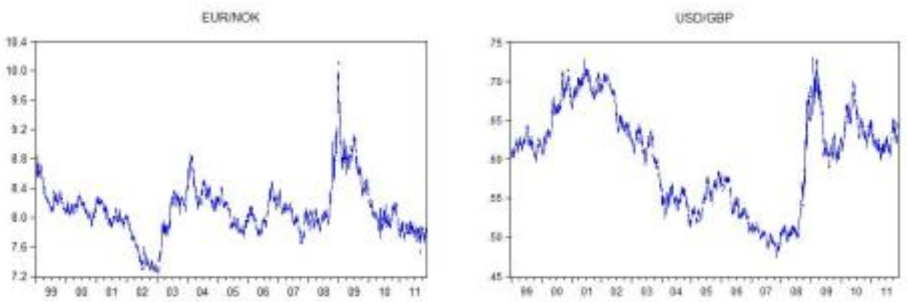
Table 2 presents the summary statistics for the daily exchange rate returns, calculated as the daily change in log spot exchange rate in percentage. This shows that both the UK sterling and the South African rand have slightly depreciated against the US dollar over the period, while the Norwegian krone has slightly appreciated against the euro.

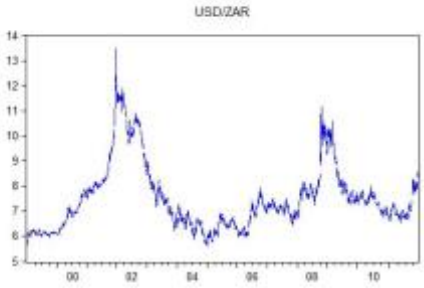
Table 2: Summary Statistics Exchange Rate Returns

Exchange rate	Mean	Std. Dev	Skew.	Kurt.	Max	Min	Obs.
EUR/NOK	-0.004	0.451	0.181	7.881	2.576	-3.809	3237
USD/ZAR	0.011	1.085	0.361	8.714	9.808	-8.523	3240
USD/GBP	0.002	0.614	0.244	9.229	6.057	-4.475	3249

Note: Table 2 presents summary statistics for daily exchange rate returns in percentage for the period 1999-2011.

Figure 1: Spot Exchange Rates





Note: Figure 1 graphs spot exchange rates for the EUR/NOK, the USD/GBP, and the USD/ZAR over the period 1999-2011.

4.3.1.2 Order Flow

Order flow is defined as the net of buyer-initiated and seller-initiated orders. If a dealer initiates a trade against another dealer`s EUR/NOK quote, and that trade is a NOK purchase (sale), then order flow is -1 (+1). Positive order flow thereby indicates a net selling pressure on the UK sterling, the Norwegian krone and the South African rand. Net purchases of the UK sterling, the Norwegian krone and the South African rand – a negative order flow – should lead to a higher dollar price of GBP and ZAR, and a higher euro price of NOK. The relationship between order flow and exchange rate returns is thereby expected to be positive. Since the variable does not reflect the size of each order, a large trade will have the same effect as a small transaction. This must be taken into consideration when using order flow as a liquidity measure.

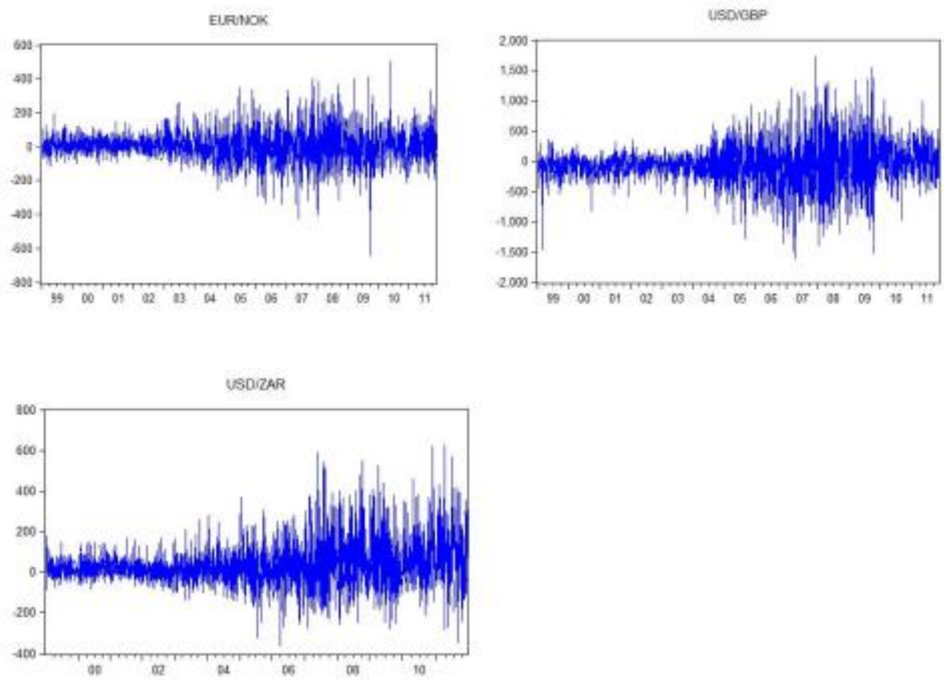
Table 3 presents the summary statistics for the daily order flow of the three currency pairs. The USD/GBP exhibit on average a daily negative order flow, while the EUR/NOK and the USD/ZAR have a daily average positive order flow over the period. This indicates that there on average was a net buying pressure on the GBP and net selling pressure of the NOK and the ZAR over the period. The USD/GBP clearly has the highest order flow in absolute value over the period. From the graphs, it is clear that order flow has increased throughout the period for all currency pairs.

Table 3: Summary Statistics Daily Order Flow

Exchange rate	Mean	Std. Dev	Skewness	Kurtosis	Max	Min	Obs.
EUR/NOK	5.07	87.18	0.016	6.307	502	-640	3237
USD/ZAR	35.39	103.5	1.025	6.301	623	-364	3240
USD/GBP	-56.20	325.9	0.097	5.860	1733	-1615	3249

Note: Table 3 presents descriptive statistics for the daily order flow in the period 1999-2011. An average order flow of e.g. 5 means that on average there are five more buys than sells during the day.

Figure 2: Daily Order Flow



Note: Figure 2 shows daily order flow for the EUR/NOK, the USD/GBP, and the USD/ZAR for the period 1999-2011.

4.3.1.3 Interest Rate Differential

The interest rate differential is calculated from the 1-month forward rate and the spot rate, using the Covered Interest Rate Parity (CIP):

$$F_t = \frac{(1+i_t^*)S_t}{(1+i_t)} \Rightarrow \ln\left(\frac{F_t}{S_t}\right) \times 100 \approx i_t^* - i_t \qquad \text{(eq. 4.1)}$$

Here, F_t is the 1-month forward rate and S_t is the spot exchange rate, defined as unit of foreign currency per unit of domestic currency. i_t^* and i_t is the foreign and domestic interest rate, respectively.

The interest rate differential should have a positive relation with the exchange rate return because an increase in e.g. the Norwegian interest rate results in a depreciation of the NOK – an increase in EUR/NOK - over the relevant period, required by uncovered interest parity (Evans and Lyons, 1999).

The summary statistics for the interest rate differential are presented in table 4. It shows that all currency pairs exhibit on average daily positive interest rate differentials, indicating that the interest rates in the U.K., Norway, and South Africa on average has been greater than the interest rates in the U.S. and the Eurozone during the period.

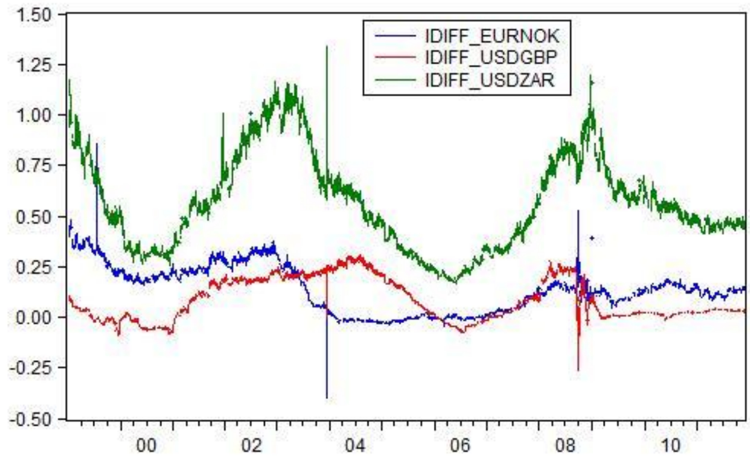
Figure 3 graphs the daily interest rate differential, showing that some days have large outliers. However, they are treated as ordinary data, since there is a lot of movement in money markets and it is therefore not obvious that these outliers represent errors. A regression using data without outliers is performed as a robustness check, and is presented in the appendix (table B). It shows that removing outliers does not have an impact on the results.

Table 4: Summary Statistics Interest Rate Differential

Exchange rate	Mean	Std. Dev	Skewness	Kurtosis	Obs.
EUR/NOK	0.135	0.114	0.362	2.809	3237
USD/ZAR	0.563	0.232	0.477	2.456	3240
USD/GBP	0.083	0.101	0.397	1.845	3249

Note: Table 4 presents summary statistics for the daily interest rate differentials for the period 1999-2011. They are calculated from the 1-month forward rate and the spot rate, using the Covered Interest Rate Parity (CIP).

Figure 3: Daily Interest Rate Differential



Note: Figure 3 graphs daily interest rate differentials for the EUR/NOK (blue), the USD/GBP (red), and the USD/ZAR (green) for the period 1999-2011.

4.3.1.4 Volume

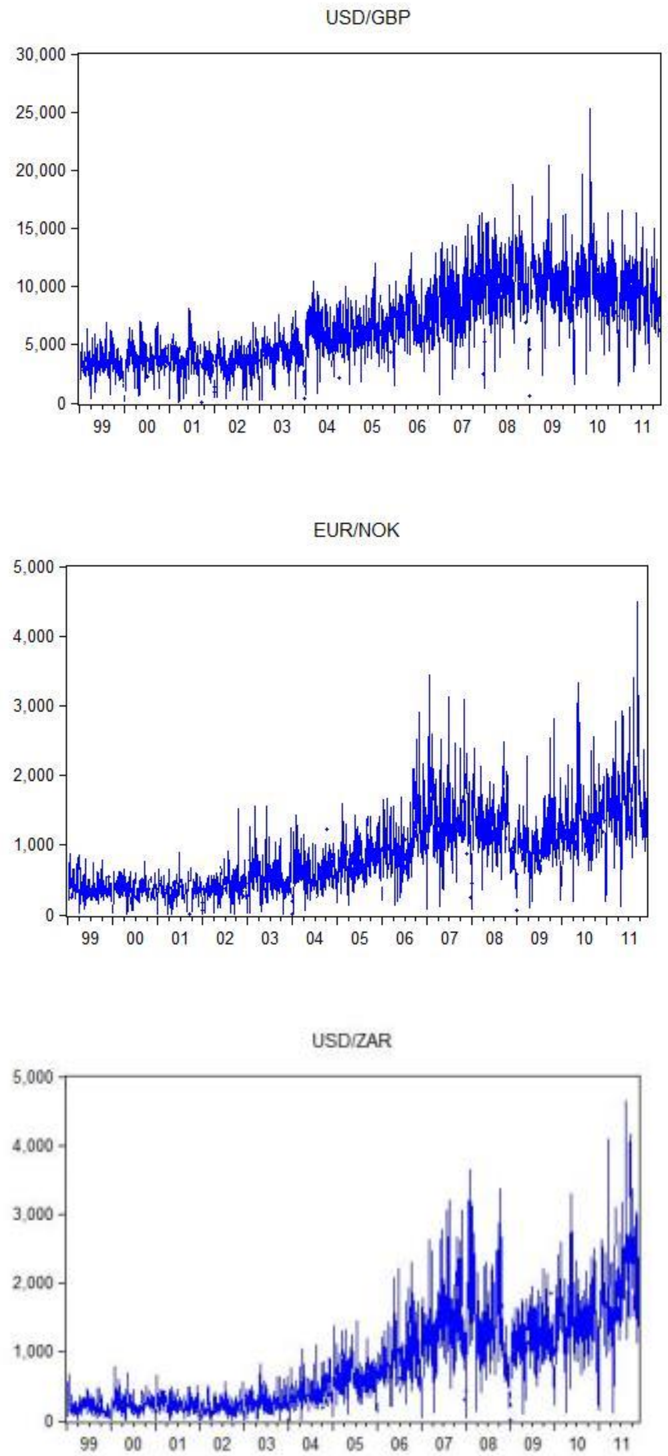
The volume variable is the sum of buy-orders and sell-orders, and is a measure of the trading activity. Figure 4 shows that the volume is clearly increasing for all currency pairs over the period. The volume of the USD/GBP is significantly higher than the volume of the EUR/NOK and the USD/ZAR, with an average of 6709 trades per day, compared to slightly over 800 for the EUR/NOK and the USD/ZAR.

Table 5: Summary Statistics Daily Number of Trades

Exchange rate	Mean	Std. Dev	Skewness	Kurtosis	Max	Obs.
EUR/NOK	847	535	1.193	5.017	4494	3235
USD/ZAR	812	694	1.193	4.367	4637	3240
USD/GBP	6709	3272	0.595	3.013	25424	3246

Note: Table 5 shows the summary statistics for the daily number of trades, calculated as the sum of buy-orders and sell-orders, for the period 1999-2011.

Figure 4: Daily Trading Volume



Note: Figure 4 graphs daily trading volume for the USD/GBP, the EUR/NOK, and the USD/ZAR for the period 1999-2011.

4.3.1.5 Bid-Ask Spread

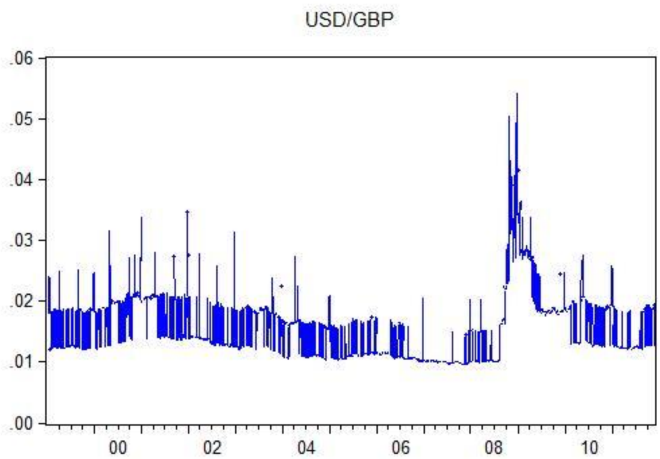
The bid-ask spread functions as a proxy for liquidity in the exchange rate, and tends to increase when liquidity decreases. Figure 5 shows the graphical representations of the relative bid-ask spreads for the three currency pairs. It shows that the spread is clearly highest for the USD/ZAR, and lowest for the USD/GBP. This discrepancy is most prominent in the period 2001-2005, and decreases afterwards. It is worth mentioning that the USD/ZAR has a considerably higher spread than the EUR/NOK, even though the trading volume is approximately the same, indicating a lower liquidity for the USD/ZAR pair.

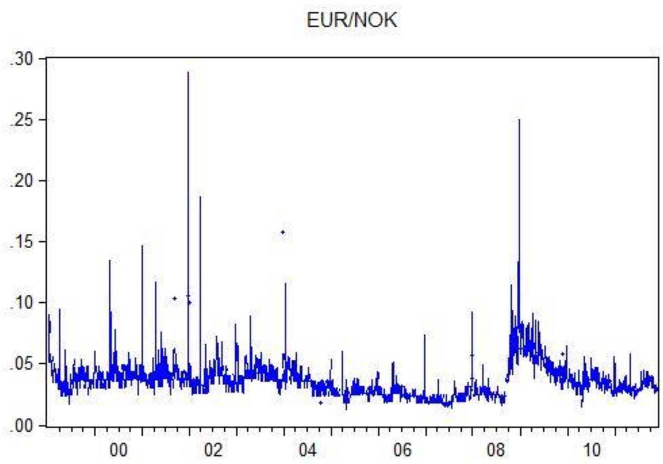
Table 6: Summary Statistics Bid-Ask Spread

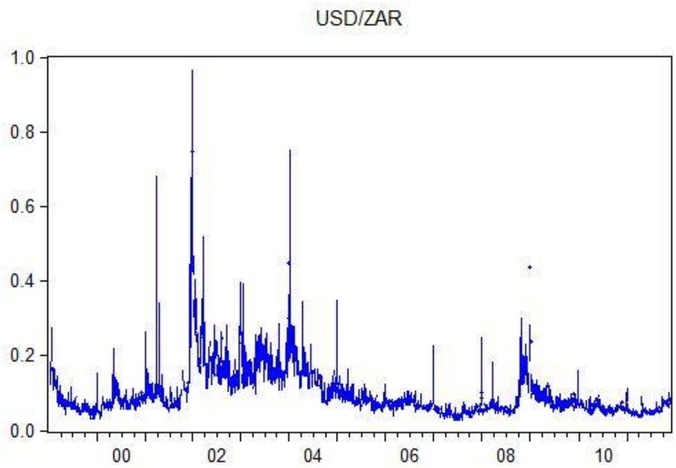
Exchange rate	Mean	Std. Dev	Skewness	Kurtosis	Obs.
EUR/NOK	0.037	0.021	19.33	646.6	3235
USD/ZAR	0.100	0.069	4.439	46.06	3240
USD/GBP	0.016	0.006	2.422	19.56	3246

Note: Table 6 presents summary statistics for the daily relative bid-ask spreads for the period 1999-2011.

Figure 5: Daily Bid-Ask Spread





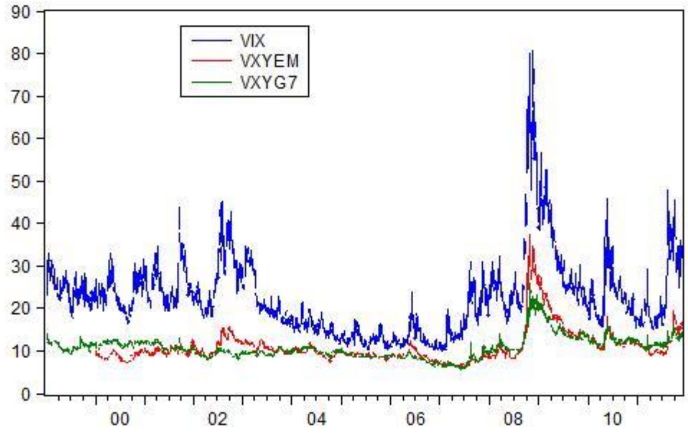


Note: Figure 5 graphs daily relative bid-ask spreads for the USD/GBP, the EUR/NOK, and the USD/ZAR over the period 1999-2011.

4.3.1.6 Volatility

As a measure of market risk, three volatility indexes are used. The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) shows the market´s expectation of 30-day volatility, and is constructed using the implied volatilities of a wide range of S&P500 index options. The VXYG7 index measures volatility in a basket of G7 currencies. The VXYEM index is a measure of volatility in emerging market currencies. VIX and VXYG7 will be used for the USD/GBP and the EUR/NOK, and VIX and VXYEM for the USD/ZAR. Figure 6 shows a graphical representation of the indexes. The average daily volatility is about 22 for VIX and 10 for VXYG7 and VXYEM, and as expected, the volatility has a peak in late-2008.

Figure 6: Volatility Indexes

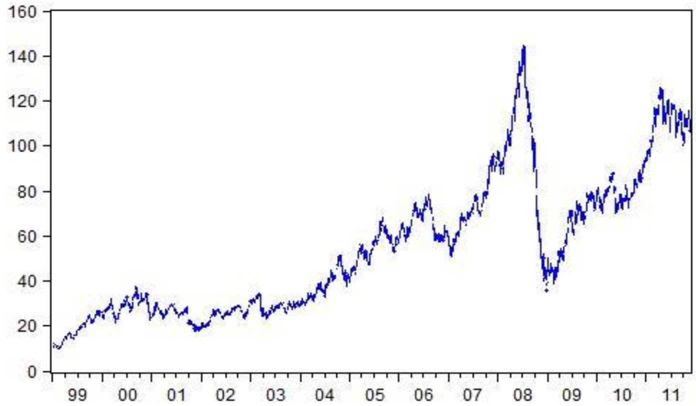


Note: The volatility indexes are quoted in annual standard deviations.

4.3.1.7 Oil Price

Figure 7 shows a steady increase in the Brent crude oil price, until a rapid and enormous fall in 2008, as expected.

Figure 7: Oil Price



Note: The Brent crude oil price is quoted in $/barrel.

4.3.2 Correlation

Table 7-9 present the correlation between the variables in data set 1. Here, Δp_t is the daily change in log spot exchange rate, measured as a percentage return, $\Delta(i_t - i_t^*)$ is the daily change in the one-day interest differential, Δx_t is the daily order flow, $\Delta spread_t$ is the daily log change in bid-ask spread, Δoil_t is the log daily change in the Brent crude oil price, $\Delta VIX_t, \Delta VXYG7_t$, and $\Delta VXYEM_t$ is the log daily change in the volatility indexes, and Δvol_t is the daily log change in trading volume.

The tables reveal a large, positive relationship between exchange rate returns and order flow, indicating that order flow can explain much of the variation in exchange rate returns. It also shows a negative relationship between change in oil price and returns, and a positive relationship between change in volatility and returns. Another thing to note is the large, negative relationship between change in volume and change in bid-ask spread. When trading volume increases, bid-ask spread decreases and liquidity increases, in line with economic intuition.

Table 7: Correlation EUR/NOK

	Δp_t	$\Delta(i_t - i_t^*)$	Δx_t	Δoil_t	$\Delta spread_t$	Δvol_t	ΔVIX_t	$\Delta VXYG7_t$
Δp_t	1.00							
$\Delta(i_t - i_t^*)$	-0.02	1.00						
Δx_t	0.58	-0.05	1.00					
Δoil_t	-0.13	0.02	-0.11	1.00				
$\Delta spread_t$	0.11	0.01	0.06	0.001	1.00			
Δvol_t	0.03	-0.005	0.05	-0.04	-0.39	1.00		
ΔVIX_t	0.09	-0.02	0.10	0.02	0.04	0.04	1.00	
$\Delta VXYG7_t$	0.15	0.01	0.11	-0.05	0.09	0.07	0.14	1.00

Note: Δp_t is the daily change in log spot exchange rate, measured as a percentage return, $\Delta(i_t - i_t^*)$ is the daily change in the one-day interest differential, Δx_t is the daily order flow, $\Delta spread_t$ is the daily log change in bid-ask spread, Δoil_t is the log daily change in the Brent crude oil price, $\Delta VIX_t, \Delta VXYG7_t$, and $\Delta VXYEM_t$ is the log daily change in the volatility indexes, and Δvol_t is the daily log change in trading volume.

Table 8: Correlation USD/GBP

	Δp_t	$\Delta(i_t - i_t^*)$	Δx_t	Δoil_t	$\Delta spread_t$	Δvol_t	ΔVIX_t	$\Delta VXYG7_t$
Δp_t	1.00							
$\Delta(i_t - i_t^*)$	-0.02	1.00						
Δx_t	0.60	0.01	1.00					
Δoil_t	-0.09	-0.02	-0.004	1.00				
$\Delta spread_t$	0.01	0.005	0.02	0.03	1.00			
Δvol_t	0.05	-0.002	0.009	-0.001	-0.30	1.00		
ΔVIX_t	0.02	-0.03	0.03	0.01	0.04	0.07	1.00	
$\Delta VXYG7_t$	0.12	-0.003	0.04	-0.04	0.09	0.10	0.13	1.00

Note: See table 7 for detailed description.

Table 9: Correlation USD/ZAR

	Δp_t	$\Delta(i_t - i_t^*)$	Δx_t	Δoil_t	$\Delta spread_t$	Δvol_t	ΔVIX_t	$\Delta VXYEM_t$
Δp_t	1.00							
$\Delta(i_t - i_t^*)$	-0.002	1.00						
Δx_t	0.52	-0.01	1.00					
Δoil_t	-0.07	0.01	-0.04	1.00				
$\Delta spread_t$	0.06	0.06	0.02	-0.02	1.00			
Δvol_t	0.12	-0.004	0.13	0.02	-0.45	1.00		
ΔVIX_t	0.17	-0.02	0.28	0.01	0.03	0.07	1.00	
$\Delta VXYEM_t$	0.31	0.03	0.14	-0.11	0.14	0.08	0.09	1.00

Note: See table 7 for detailed description.

4.4 Data set 2

The variables to be analysed on an intradaily frequency in the second part of the thesis include exchange rate returns, order flow, bid-ask spread, and volume. Descriptive statistics and correlations follows below.

4.4.1 Descriptive statistics

4.4.1.1 Exchange Rate Returns

Table 10 presents the summary statistics for the intradaily exchange rate returns, calculated as the change in log spot exchange rate in percentage. For the EUR/NOK there seems to be a tendency for appreciation of the NOK against the EUR at evening- and nighttime, and depreciation at daytime. The GBP appreciates against the USD at evening and nighttime, and depreciates at daytime. This is consistent with previous research, which find that local currencies tend to depreciate during their own trading hours and appreciate outside them (Breedon and Ranaldo, 2013). The ZAR depreciates against the USD at night and appreciates during the day and evening.

The period between 07 and 18 GMT exhibits the highest standard deviations for all currency pairs. At evening and night, the volatility is far lower. This is in line with French and Roll´s study on equity returns, where they found that prices are more variable during exchange trading hours than during non-trading hours (French and Roll, 1986). It is also consistent with Ito and Lin´s hourly analysis of Tokyo (TSE) and New York (NYSE) stock markets. They revealed lower variances during the lunch hours in Tokyo than during other hours. They also found the variance ratio of lunch hour returns to other trading time returns to be lower in Tokyo than in New York. Since trading continues during lunch hours in the NYSE, smaller variance ratios in the NYSE suggest that the low rate of public information during lunch hours cannot solely explain the lower variance during the lunch hours in the TSE (Ito and Lin, 1992). Likewise, King, Osler and Rime (2012) have reported that trading volume decreases during lunch hours. These findings therefore suggest that the existence of trading itself increases volatility, which also seems to be the case here.

Another thing to notice is the skewness of returns. There are large differences in the skewness throughout the day. Returns in the evening for the USD/GBP are highly negatively skewed, while returns in the evening and night for the USD/ZAR are highly positively skewed.

Table 10: Summary Statistics Intradaily Exchange Rate Returns

	Mean	Std. Dev	Skewness	Kurtosis	Max	Min	Obs.
			EUR/NOK				
Day	0.017	0.441	0.199	8.172	3.320	-3.299	4181
Evening	-0.006	0.157	0.314	21.05	2.229	-1.697	4340
Night	-0.008	0.143	-0.228	11.66	1.305	-1.430	4170
			USD/GBP				
Day	0.017	0.495	0.244	5.585	3.487	-2.374	4390
Evening	-0.013	0.205	-2.164	38.68	1.441	-3.189	4409
Night	-0.006	0.190	0.590	15.39	2.410	-1.423	4394
			USD/ZAR				
Day	-0.007	0.982	-0.773	18.54	5.401	-12.61	3806
Evening	-0.010	0.456	2.515	88.30	10.61	-5.105	4074
Night	0.032	0.461	5.635	150.5	12.46	-3.931	3783

Note: Table 10 presents summary statistics for the intradaily exchange rate returns for the period 1999-2015, calculated as the change in log spot exchange rate in percentage.

4.4.1.2 Order Flow

Order flow is measured as in data set 1: Positive order flow implies a net selling pressure on the Norwegian krone, the UK sterling, and the South African rand.

Order flow has its highest and lowest values for the USD/GBP pair, and spans from -1578 to 1856. The average order flows are negative for the USD/GBP and positive for the EUR/NOK and the USD/ZAR, for all periods of the day, implying a positive demand for GBP and a negative demand for NOK and ZAR in the period under investigation. Order flow has its highest absolute values at daytime for all currency pairs, and it is also in this period the standard deviations are largest. The large standard deviations allow for negative (positive) order flows for the EUR/NOK and the USD/ZAR (USD/GBP) and positive (negative) demand for NOK and ZAR (GBP) in certain periods of time during the sample.

Table 11: Summary Statistics Intradaily Order Flow

	Mean	Std. Dev	Skewness	Kurtosis	Max	Min	Obs.
				EUR/NOK			
Day	5.417	84.16	0.008	5.695	451	-632	4371
Evening	1.123	16.21	0.338	7.398	121	-86	4344
Night	0.048	12.02	1.106	16.09	128	-78	4187
				USD/GBP			
Day	-20.46	297.6	0.119	6.081	1856	-1578	4431
Evening	-5.000	61.54	0.322	28.58	1052	-631	5248
Night	-9.186	68.45	-0.181	8.111	543	497	4395
				USD/ZAR			
Day	34.57	102.7	0.779	5.376	606	-352	4132
Evening	0.923	21.81	0.093	17.87	219	-247	4147
Night	1.450	15.52	0.668	9.265	98	-94	3812

Note: Table 11 presents descriptive statistics for intradaily order flow for the period 1999-2015. An average order flow of e.g. 5 means that on average there are five more buys than sells.

4.4.1.3 Volume

The highest average trading volume occurs at daytime for all currency pairs, as expected. For the USD/ZAR and the EUR/NOK the lowest average trading volume is at night. For the USD/GBP, the average daily trading volume is quite similar in the evening and night, with a slightly higher number at night. This makes sense, since U.S. trading hours are 5-10 hours shifted backwards relative to European trading hours.

Table 12: Summary Statistics Intradaily Trading Volume

	Mean	Std. Dev	Skewness	Kurtosis	Max	Obs.
			EUR/NOK			
Day	933	561	1.096	5.486	4704	4371
Evening	60	52	2.144	12.05	540	4344
Night	26	29	5.008	72.59	670	4187
			USD/GBP			
Day	5797	2889	0.620	3.292	21274	4431
Evening	498	423	2.299	14.38	5085	5249
Night	527	390	3.193	34.61	7566	4395
			USD/ZAR			
Day	1029	872	0.975	3.428	5310	4132
Evening	62	75	4.950	56.36	1412	4147
Night	34	39	2.648	16.61	536	3812

Note: Table 12 shows summary statistics for the intradaily number of trades, calculated as the sum of buy-orders and sell-orders, for the period 1999-2015.

4.4.1.4 Bid-Ask Spread

For the EUR/NOK and the USD/ZAR the average relative bid-ask spread is lowest at daytime and highest at night, indicating lower liquidity during the night. For the USD/GBP the highest spread is at daytime. However, the variations in the bid-ask spread for the USD/GBP is very small compared to the EUR/NOK and the USD/ZAR. This shows that liquidity is close to constant throughout the day for the USD/GBP pair, indicating low liquidity risk even during the night.

Table 13: Summary Statistics Intradaily Bid-Ask Spread

	Mean	Std. Dev	Skewness	Kurtosis	Obs.
			EUR/NOK		
Day	0.039	0.039	29.38	1245	4377
Evening	0.068	0.041	6.268	84.30	4362
Night	0.096	0.067	7.846	149.8	4385
			USD/GBP		
Day	0.034	0.087	5.952	49.23	4673
Evening	0.025	0.021	8.018	119.1	5259
Night	0.022	0.040	36.89	1481	4398
			USD/ZAR		
Day	0.124	0.249	10.34	165.3	4270
Evening	0.172	0.164	10.59	245.1	4244
Night	0.228	0.216	9.805	250.0	4103

Note: Table 13 presents summary statistics for the intradaily relative bid-ask spreads for the period 1999-2015.

Looking at both the bid-ask spread and the volume variable, the least liquid periods of the day seem to be at night and in the evening.

4.4.2 Correlation

Table 14-16 present the correlation between intradaily exchange rate returns and order flow, and the first-order serial correlation of the order flow time series. $\Delta p_{day,t}$, $\Delta p_{evening,t}$, and $\Delta p_{night,t}$ is the change in log spot exchange rate at day, evening, and night, measured as a percentage return, and $\Delta \mathrm{x}_{\mathrm{day,t}}$, $\Delta \mathrm{x}_{\mathrm{evening,t}}$, and $\Delta \mathrm{x}_{\mathrm{night,t}}$ is the order flow at day, evening, and night. $\Delta x_{day,t-1}$ is the order flow the preceding night, $\Delta x_{evening,t-1}$ is the order flow the preceding day, and $\Delta x_{night,t-1}$ is the order flow the preceding evening.

The tables reveal positive and high correlation between exchange rate returns and order flow within the same period, all above 0.50. This shows that order flow can explain much of the variations in the exchange rates. The first-order serial correlation of order flow (correlation with the previous period) ranges primarily from seven to 16 percent, except for the order flow at night for the EUR/NOK, which is only 0.01 percent. The correlations between returns and order flow in the previous period are mixed, revealing no clear relationship.

Table 14: Correlation EUR/NOK

	$\Delta p_{day,t}$	$\Delta p_{evening,t}$	$\Delta p_{night,t}$	$\Delta x_{day,t}$	$\Delta x_{evening,t}$	$\Delta x_{night,t}$
$\Delta x_{day,t}$	0.60					
$\Delta x_{evening,t}$		0.51				
$\Delta x_{night,t}$			0.50			
$\Delta x_{day,t-1}$	-0.02			0.10		
$\Delta x_{evening,t-1}$		0.004			0.09	
$\Delta x_{night,t-1}$			-0.13			0.01

Note: $\Delta p_{day,t}$ is the return at daytime, $\Delta p_{evening,t}$ is the return in the evening, and $\Delta p_{night,t}$ is the return at nighttime. $\Delta x_{day,t}$ is the order flow at daytime, $\Delta x_{evening,t}$ is the order flow in the evening, and $\Delta x_{night,t}$ is the order flow at nighttime. $\Delta x_{day,t-1}$ is the order flow the preceding night, $\Delta x_{evening,t-1}$ is the order flow the preceding day, and $\Delta x_{night,t-1}$ is the order flow the preceding evening.

Table 15: Correlation USD/GBP

	$\Delta p_{day,t}$	$\Delta p_{evening,t}$	$\Delta p_{night,t}$	$\Delta x_{day,t}$	$\Delta x_{evening,t}$	$\Delta x_{night,t}$
$\Delta x_{day,t}$	0.61					
$\Delta x_{evening,t}$		0.54				
$\Delta x_{night,t}$			0.64			
$\Delta x_{day,t-1}$	-0.02			0.15		
$\Delta x_{evening,t-1}$		-0.001			0.13	
$\Delta x_{night,t-1}$			0.03			0.12

Note: See table 14 for detailed description.

Table 16: Correlation USD/ZAR

	$\Delta p_{day,t}$	$\Delta p_{evening,t}$	$\Delta p_{night,t}$	$\Delta x_{day,t}$	$\Delta x_{evening,t}$	$\Delta x_{night,t}$
$\Delta x_{day,t}$	0.55					
$\Delta x_{evening,t}$		0.59				
$\Delta x_{night,t}$			0.51			
$\Delta x_{day,t-1}$	-0.06			0.09		
$\Delta x_{evening,t-1}$		0.05			0.16	
$\Delta x_{night,t-1}$			-0.06			0.07

Note: See table 14 for detailed description.

5. Analysis and Results

The empirical analysis will be split into two parts. The first part will look at the explanatory power of order flow on exchange rate determination using daily data (data set 1). The second part will more specifically investigate how the relationship between order flow and exchange rate returns varies during the day by analysing intradaily data (data set 2). The second part is also extended by looking at order flow impact during the world financial crisis and on holidays.

Each section will include a presentation of the regressions to be performed, residual diagnostics, presentation and interpretation of results, and a discussion in the end. The analysis and results are based on OLS regressions.

5.1 The Explanatory Power of Order Flow

5.1.1 Regressions

To investigate the relationship between exchange rate returns and order flow, both models based on macro fundamentals alone, microstructure models, and hybrid models are used. The seven regressions to be performed are inspired by Evans and Lyons (2002) and Evans and Rime (2016), among others. The dependent variable Δp_t is the daily change in log spot exchange rate, measured as a percentage return. The estimated regressions are as follows:

1. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \varepsilon_t$
2. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta oil_t + \beta_3 \Delta V_t + \varepsilon_t$
3. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta oil_t + \beta_3 \Delta spread_t + \beta_4 \Delta V_t + \beta_5 \Delta vol_t + \varepsilon_t$
4. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \varepsilon_t$
5. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta oil_t + \beta_3 \Delta V_t + \beta_4 \Delta x_t + \varepsilon_t$
6. $\Delta p_t = \alpha + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta oil_t + \beta_3 \Delta spread_t + \beta_4 \Delta V_t + \beta_5 \Delta vol_t + \beta_6 \Delta x_t + \varepsilon_t$
7. $\Delta p_t = \alpha + \beta_1 \Delta x_t + \varepsilon_t$ (eq. 5.1.1-5.1.7)

Here, $\Delta(i_t - i_t^*)$ is the daily change in the one-day interest rate differential, Δx_t is the daily order flow, $\Delta spread_t$ is the log daily change in bid-ask spread, Δoil_t is the log daily change in the Brent crude oil price, ΔV_t is the log daily change in the volatility index, and Δvol_t is the log daily change in trading volume.

The coefficient on order flow measures the impact of a one-standard deviation change in order flow.

5.1.2 Residual Diagnostics

To test for heteroscedasticity in the residuals, the White (1980) and the Engle Lagrange Multiplier (LM) (1982) test for ARCH effects in the residuals are performed. It is clear that most of the regression residuals are heteroscedastic (row (k) and (l) in table 17-19).

The Breusch-Godfrey LM (1978) test is performed to test for the presence of serial correlation in the residuals. For the USD/ZAR there is no evidence of autocorrelation, while there for the USD/GBP and the EUR/NOK are signs of autocorrelation in some of the regression residuals (row (m) in table 17-19).

To correct for heteroscedasticity and autocorrelation in the residuals, standard errors are adjusted with the Newey-West (1987) procedure.

5.1.3 Results and Interpretation

Table 17-19 report results from estimated regressions 5.1.1-5.1.7. The coefficients are reported with t-statistics in parenthesis. Regressing the daily change in the log spot exchange rate on only the log change in the interest rate differential, provides R^2 values below one percent for all currency pairs and yield no statistical significant variables even at the 10 percent level.

The macro model with log change in interest rate differential, oil price, and volatility as explanatory variables, yield an R^2 of maximum 11.7 percent. Including microstructure variables such as bid-ask spread and trading volume almost has no effect on the explanatory power. For all currency pairs the oil price coefficient is negative and significant, and coefficients on the volatility indexes and volume are positive and significant. This indicates that an increase in oil price causes the NOK, the GBP and the ZAR to appreciate against the EUR and the USD respectively, and that an increase in volatility and trading volume causes depreciations of the same currencies. The bid-ask spread coefficient is also positive and significant for the EUR/NOK and the USD/ZAR.

When including order flow as explanatory variable in the regressions, the explanatory power increases dramatically. It yields R^2 of about 34 percent (EUR/NOK), 33 percent (USD/ZAR), and 38 percent (USD/GBP) in equation 5.1.6. The order flow coefficient is positive and statistically significant at one percent level for all currency pairs. This indicates that an increase in order flow causes the price of the USD relative to the GBP and the ZAR, and the price of the EUR relative to the NOK, to increase. When order flow increases with one standard deviation, the EUR/NOK, USD/GBP and USD/ZAR increase by about 0.24, 0.34, and 0.54 percent, respectively. This implies that if there is a large buying pressure in the market and the volume of currency bought is higher than that of the currency sold, this will lead to the currency in question appreciating, which is in line with economic theory. These results strongly demonstrate that an increase in net buying pressure leads to higher prices, and that order flow is a significant determinant of exchange rates, in accordance with previous research.

Table 17: Regression Result USD/GBP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	0.003	-0.0004	-0.005	0.066***	0.064***	0.061***	0.066***
(a)	(0.31)	(-0.03)	(-0.37)	(7.04)	(6.24)	(6.02)	(7.00)
Δx_t				0.37***	0.34***	0.34***	0.37***
(b)				(25.73)	(29.93)	(29.93)	(25.69)
$\Delta(i_t - i_t^*)$	-0.001	-0.001	-7x10^-4	-0.001	-0.001*	-0.001*	
(c)	(-1.31)	(-1.06)	(-1.05)	(-1.34)	(-1.71)	(-1.70)	
$\Delta spread_t$			0.055			0.021	
(d)			(0.72)			(0.33)	
Δoil_t		-2.02***	-2.03***		-1.98***	-1.98***	
(e)		(-3.57)	(-3.57)		(-3.95)	(-3.93)	
ΔVIX_t		0.10	0.074		-0.048	-0.070	
(f)		(0.46)	(0.33)		(-0.28)	(-0.41)	
ΔVXYG7		2.73***	2.58**		2.21**	2.09**	
(g)		(2.65)	(2.50)		(2.53)	(2.39)	
Δvol_t			0.065**			2.09**	
(h)			(2.29)			(2.39)	
R^2	0.001	0.021	0.022	0.365	0.380	0.381	0.364
(i)	0.000	0.019	0.020	0.364	0.379	0.380	0.363
White (j)	0.03	0.19	0.00	0.00	0.00	0.00	0.00
ARCH	0.00	0.00	0.11	0.00	0.12	0.13	0.00
(k)	0.00	0.00	0.13	0.00	0.16	0.15	0.00
B-G	0.04	0.14	0.08	0.31	0.10	0.11	0.53
(l)	0.04	0.36	1.00	0.03	1.00	1.00	0.05

Note: Specification (a) is the constant term. (b) is order flow between day t-1 and t. The coefficient measures the impact of a one-standard deviation change in order flow. (c) denotes the log change in one-day interest differential from day t-1 to t. (d) is the log daily change in bid-ask spread. (e) denotes the log change in oil price from day t-1 to t. (f) is the log change in the VIX from day t-1 to t. (g) is the log change in the VXYG7 from day t-1 to t. (h) is the log daily change in trading volume. T-statistics are shown in parentheses. Specification (i) shows the R^2 and the adjusted R^2. (j) and (k) present p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (l), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

Table 18: Regression Result EUR/NOK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	-0.004	0.004	-0.003	-0.019***	-0.018**	-0.022***	-0.019***
(a)	(-0.50)	(0.48)	(-0.31)	(-3.00)	(-2.33)	(-2.95)	(-3.01)
Δx_t				0.26***	0.25***	0.24***	0.26***
(b)				(27.90)	(24.51)	(24.43)	(28.48)
$\Delta(i_t - i_t^*)$	$-2\text{x}10^{-4}$	$-3\text{x}10^{-4}$	$-3\text{x}10^{-4}$	$2\text{x}10^{-4}$	$1\text{x}10^{-4}$	$1\text{x}10^{-4}$	
(c)	(-0.76)	(-0.97)	(-1.05)	(0.84)	(0.55)	(0.45)	
$\Delta spread_t$			0.29***			0.19***	
(d)			(5.59)			(4.32)	
Δoil_t		-2.15***	-2.16***		-1.13***	-1.15***	
(e)		(-5.12)	(-5.13)		(-3.12)	(-3.18)	
ΔVIX_t		0.53***	0.50***		0.17	0.16	
(f)		(3.23)	(3.04)		(1.30)	(1.17)	
ΔVXYG7		2.39***	2.14***		1.40**	1.26*	
(g)		(3.06)	(2.71)		(1.99)	(1.77)	
Δvol_t			0.053**			0.022	
(h)			(2.41)			(1.20)	
R^2	0.000	0.041	0.053	0.326	0.343	0.349	0.328
(i)	0.000	0.039	0.050	0.325	0.342	0.347	0.327
White (j)	0.74	0.00	0.00	0.01	0.00	0.00	0.00
ARCH	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(k)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B-G	0.00	0.00	0.00	0.13	0.11	0.11	0.15
(l)	0.07	0.01	0.01	1.00	0.14	0.13	1.00

Note: Specification (a) is the constant term. (b) is order flow between day t-1 and t. The coefficient measures the impact of a one-standard deviation change in order flow. (c) denotes the change in one-day interest differential from day t-1 to t. (d) is the log daily change in bid-ask spread. (e) denotes the log change in oil price from day t-1 to t. (f) is the log change in the VIX from day t-1 to t. (g) is the log change in the VXYG7 from day t-1 to t. (h) is the log daily change in trading volume. T-statistics are shown in parentheses. Specification (i) shows the R^2 and the adjusted R^2. (j) and (k) present p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (l), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

Table 19: Regression Result USD/ZAR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	0.012	0.023	-0.002	-0.181***	-0.178***	-0.189***	-0.183***
(a)	(0.61)	(1.04)	(-0.08)	(-10.89)	(-8.29)	(-9.06)	(-10.96)
$\Delta \mathbf{x_t}$				0.56***	0.51***	0.50***	0.56***
(b)				(22.98)	(18.80)	(18.42)	(22.99)
$\Delta(\mathbf{i_t} - \mathbf{i_t^*})$	0.005	-0.002	-0.002	0.004	-0.001	$-1\text{x}10^{-4}$	
(c)	(0.92)	(-0.29)	(-0.45)	(0.98)	(-0.22)	(-0.35)	
$\Delta \mathbf{spread_t}$			0.43**			0.27*	
(d)			(2.53)			(1.73)	
$\Delta \mathbf{oil_t}$		-1.87*	-2.03*		-1.11	-1.19	
(e)		(-1.75)	(-1.92)		(-1.14)	(-1.23)	
$\Delta \mathbf{VIX_t}$		2.60***	2.47***		0.24	0.21	
(f)		(6.81)	(6.60)		(0.63)	(0.56)	
ΔVXYEM		13.04***	12.17***		10.55***	10.10***	
(g)		(7.63)	(7.45)		(5.51)	(5.48)	
$\Delta \mathbf{vol_t}$			0.26***			0.12**	
(h)			(4.27)			(2.38)	
$\mathbf{R^2}$	0.000	0.117	0.128	0.271	0.326	0.328	0.270
(i)	0.000	0.115	0.126	0.270	0.324	0.326	0.270
White (j)	0.03	0.00	0.00	0.00	0.00	0.00	0.00
ARCH	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(k)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B-G	0.42	0.57	0.45	0.60	0.17	0.24	0.59
(l)	0.87	0.87	0.98	1.00	0.48	0.60	1.00

Note: Specification (a) is the constant term. (b) is order flow between day t-1 and t. The coefficient measures the impact of a one-standard deviation change in order flow. (c) denotes the change in one-day interest rate differential from day t-1 to t. (d) is the log daily change in bid-ask spread. (e) denotes the log change in oil price from day t-1 to t. (f) is the log change in the VIX from day t-1 to t. (g) is the log change in the VXYEM from day t-1 to t. (h) is the log daily change in trading volume. T-statistics are shown in parentheses. Specification (i) shows the R^2 and the adjusted R^2. (j) and (k) present p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (l), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

At first sight it seems like order flow has much higher impact on prices for the USD/ZAR pair than for the other two. However, when comparing one standard deviation change in order flow with one standard deviation change in exchange rate returns in table 20, it is clear that this is not the case. Order flow impact is actually lower for the USD/ZAR pair, and highest for the USD/GBP pair. This is somewhat surprising, since the USD/ZAR is characterized as the least liquid currency pair among the three, and the USD/GBP as the most liquid currency pair.

Table 20: Comparing Order Flow with Standard Deviation of Returns

	EUR/NOK	USD/GBP	USD/ZAR
Order flow coefficient	0.24	0.34	0.50
Standard deviation of returns	0.45	0.61	1.09
Ratio	*0.53*	*0.56*	*0.46*

Table 20 compares order flow coefficients from equation 5.1.6 and daily standard deviation of exchange rate returns. The order flow coefficient measures the impact of a one-standard deviation change in order flow.

5.1.4 Discussion

The overall results are in line with initial expectations. Order flow performs well in explaining exchange rate dynamics, and seems to be a significant determinant of prices in the foreign exchange market. It is therefore plausible to conclude that order flow conveys relevant information.

This relation between order flow and exchange rates is not necessarily inconsistent with the macro approach. The fact that order flow seems to be the proximate determinant for exchange rates does not exclude macro fundamentals from being the underlying determinant. Order flow may simply be a better "proxy" for fundamentals that are hard to measure precisely. Measures of e.g. expectations done through surveys are obviously imprecise. Order flow, on the other hand, represents expectations based on real actions, and reflect a willingness to back one`s beliefs with real money.

5.2 The Intradaily Relationship between Order Flow and Exchange Rate Returns

The foreign exchange market is a highly liquid market, and is thereby believed to be the most efficient financial market. However, this does not mean that currencies are not subject to varying liquidity conditions that must be kept in mind.

In this section, the intradaily relationship between order flow and exchange rates is addressed. The analysis compares periods with low trading activity with periods with high trading activity, and thereby gives insight into how the liquidity of the FX market affects prices. Prices in a highly liquid market have a tendency to move gradually and in small increments. In a less liquid market, prices tend to move more abruptly and in larger increments. It is therefore expected that order flow will have a larger impact on prices in less liquid periods of the day.

5.2.1 Regressions

The estimated regressions to explore the intradaily relationship between exchange rate returns and order flow are the following:

1. $\Delta p_t = \alpha + \beta_1 \Delta x_t + \varepsilon_t$
2. $\Delta p_t = \alpha + \beta_1 \Delta x_t + \beta_2 \Delta spread_t + \beta_3 \Delta vol_t + \varepsilon_t$ (eq. 5.2.1-5.2.2)

Here, Δp_t is the intradaily exchange rate percentage log-return, Δx_t is the order flow between t-1 and t, $\Delta spread_t$ is the log change in bid-ask spread between time t-1 and t, and Δvol_t is the log change in trading volume between t-1 and t.

The regressions are run for the three intradaily periods - day, night, and evening - for each currency pair. The coefficient on order flow measures the impact of a one-standard deviation change in order flow.

5.2.2 Residual Diagnostics

The heteroscedasticity tests reveal clear signs of heteroscedastic regression residuals. There are also signs of autocorrelation in some of the regression residuals for all currency pairs (table 21-23, row f-h). To correct for heteroscedasticity and autocorrelation in the residuals, standard errors are adjusted with the Newey-West (1987) procedure.

5.2.3 Results and Interpretation

Table 21 reports results for the EUR/NOK pair. It shows that order flow is highly significant and the explanatory power varies from 21.8 to 25.7 percent. The order flow coefficient varies from 0.07 at evening and night to 0.22 at daytime. In other words, order flow has three times more impact on returns at daytime than in the evening and at night. Bid-ask spread increases and volume decreases the exchange rate in the evening.

Table 21: Regression Result EUR/NOK

Time	Day		Evening		Night	
Model	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Const.	0.003	0.007	-0.01***	-0.04***	-0.008***	-0.01***
(a)	(0.45)	(0.27)	(-5.51)	(-3.66)	(-4.32)	(-3.01)
Δx_t	0.22***	0.22***	0.07***	0.07***	0.07***	0.07***
(b)	(38.00)	(26.59)	(36.57)	(18.36)	(34.08)	(20.84)
$\Delta spread_t$		$2x10^{-4}$		$1x10^{-4}$*		$2x10^{-5}$
(c)		(1.38)		(1.85)		(0.49)
Δvol_t		$4x10^{-5}$		$-7x10^{-5}$**		$-5x10^{-6}$
(d)		(0.60)		(-1.98)		(-0.23)
R^2	0.257	0.257	0.235	0.237	0.218	0.218
(e)	0.256	0.257	0.235	0.236	0.218	0.218
White	0.00	0.00	0.00	0.00	0.00	0.00
(f)						
ARCH	0.00	0.00	0.00	0.00	0.08	0.07
(g)	0.00	0.00	0.00	0.00	0.28	0.00
B-G	0.00	0.00	0.00	0.00	0.08	0.12
(h)	0.00	0.00	0.02	0.02	0.44	0.61

Note: Specification (a) is the constant term. (b) is the intradaily order flow between time t-1 and t. The coefficient measures the impact of a one-standard deviation change in order flow. (c) is the log change in bid-ask spread from t-1 to t. (d) is the log change in trading volume from t-1 to t. T-statistics are shown in parentheses. Specification (e) shows the R^2 and the adjusted R^2. (f) and (g) present the p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (h), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

Regression results for the USD/GBP are presented in table 22, with R^2 from 27.7 to 40.5 percent. Bid-ask spread has a positive impact on returns in the evening. The order flow coefficients are highly significant at 1 percent level for all periods, with a coefficient of 0.3 at daytime. This indicates that when order flow increases with one standard deviation, the USD/GBP exchange rate increase by 0.3 percent. As for the EUR/NOK, the coefficients at evening and night is far lower. Again, order flow has lower impact on exchange rates at evening and night.

Table 22: Regression Result USD/GBP

Time	**Day**		**Evening**		**Night**	
Model	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Const.	0.04***	-0.006	-0.003	0.004	0.01***	0.01***
(a)	(5.56)	(-0.27)	(-0.87)	(0.30)	(4.54)	(4.51)
Δx_t	0.30***	0.30***	0.10***	0.10***	0.12***	0.12***
(b)	(34.25)	(34.12)	(13.56)	(13.50)	(27.50)	(27.43)
$\Delta spread_t$		$-2x10^{-4}$		$2x10^{-4}$*		$7x10^{-5}$
(c)		(-0.83)		(1.66)		(0.78)
Δvol_t		$2x10^{-4}$		$5x10^{-5}$		$4x10^{-5}$
(d)		(1.44)		(0.83)		(1.25)
R^2	0.369	0.370	0.277	0.288	0.404	0.405
(e)	0.369	0.370	0.277	0.287	0.404	0.405
White	0.00	0.00	0.00	0.00	0.00	0.00
(f)						
ARCH	0.00	0.00	0.00	0.00	0.00	0.00
(g)	0.00	0.00	0.00	0.00	0.00	0.00
B-G	0.00	0.00	0.78	0.64	0.01	0.01
(h)	0.00	0.00	0.28	0.19	1.00	0.96

Note: See table 21 for detailed description.

Table 23 reveals similar results for the USD/ZAR pair, with statistically significant (at one percent level) and high order flow coefficients from 0.23 at nighttime and 0.25 in the evening, to 0.50 at daytime. The coefficient on volume is positive and significant at daytime, but very close to zero.

Table 23: Regression Result USD/ZAR

Time	Day		Evening		Night	
Model	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Const.	-0.19***	-0.36***	-0.022***	-0.04	0.011*	0.012
(a)	(-13.05)	(-5.42)	(-3.69)	(-1.38)	(1.73)	(1.25)
Δx_t	0.50***	0.50***	0.26***	0.25***	0.22***	0.22***
(b)	(38.48)	(28.13)	(44.65)	(13.17)	(34.33)	(22.87)
$\Delta spread_t$		$2x10^{-4}$		$3x10^{-4}$		$2x10^{-4}$
(c)		(0.43)		(0.93)		(1.30)
Δvol_t		$5x10^{-4}$***		$-2x10^{-5}$		$1x10^{-4}$
(d)		(2.67)		(-0.16)		(1.28)
R^2	0.280	0.282	0.329	0.329	0.238	0.239
(e)	0.280	0.281	0.329	0.329	0.237	0.238
White	0.32	0.00	0.00	0.00	0.67	0.46
(f)						
ARCH	0.00	0.00	0.00	0.00	0.86	0.87
(g)	0.00	0.00	0.00	0.00	0.00	0.00
B-G	0.19	0.30	0.00	0.00	0.01	0.01
(h)	0.00	0.01	0.00	0.00	0.52	0.52

Note: See table 21 for detailed description.

It is obvious from the regression results that the variation in order flow´s impact on exchange rates throughout the day is highly statistically significant for all currency pairs. However, what is relevant when drawing a conclusion is the economic significance. To evaluate the economic implication, the order flow coefficients are compared with the normal standard deviation of the exchange rate returns in table 24. When doing so, it is revealed that the higher order flow impact at daytime can be explained by the higher standard deviations of exchange rate returns at daytime. For the EUR/NOK and the USD/ZAR, the ratio of order flow to standard deviation is approximately the same at day- and nighttime, indicating that order flow impact does not differ between day and night. The USD/GBP shows a similar pattern, with a bit higher ratio at nighttime. Order flow impact is lower for the EUR/NOK and the USD/GBP, and higher for the USD/ZAR, in the evening.

From the descriptive statistics, it was concluded that the least liquid periods of the day are in the evening and at night. My expectation was therefore that order flow impact would be larger in the evening and at night. The results for the EUR/NOK and the USD/GBP are thereby inconsistent with initial expectations. For the USD/ZAR, the higher order flow impact in the evening is in line with initial expectations, but I would expect this to be the case also at night.

Altogether, when evaluating all currency pairs, there are no clear signs of a definite pattern in the order flow impact. Similar ratios at daytime and nighttime indicate that the liquidity in the market has no distinct influence on buying pressure´s impact on prices. The conclusion is therefore that the variation in order flow´s impact between liquid and less liquid periods is highly statistically significant, but not evidently economically significant.

Table 24: Comparing Order Flow with Standard Deviation of Returns

	Day	**Evening**	**Night**
		EUR/NOK	
Order flow coefficient	0.22	0.07	0.07
Std. dev. of returns	0.44	0.16	0.14
Ratio	*0.50*	*0.44*	*0.50*
		USD/GBP	
Order flow coefficient	0.30	0.10	0.12
Std. dev. of returns	0.50	0.21	0.19
Ratio	*0.60*	*0.48*	*0.63*
		USD/ZAR	
Order flow coefficient	0.50	0.26	0.23
Std. dev. of returns	0.98	0.46	0.46
Ratio	*0.51*	*0.57*	*0.50*

Note: Table 24 compares order flow coefficients from equation 5.2.1 and standard deviation of exchange rate returns for daytime, evening, and nighttime. The order flow coefficient measures the impact of a one-standard deviation change in order flow.

5.2.4 Feedback and Anticipation Effects

To be able to capture important dynamic structures in the exchange rate and further investigate the order flow impact, the analysis is extended by adding lags of the explanatory and explained variables. The following regression is tested:

$$\Delta p_t = \alpha + \beta_1 \Delta x_t + \beta_2 \Delta x_{t-1} + \beta_3 \Delta p_{t-1} + \varepsilon_t \qquad \text{(eq. 5.2.3)}$$

The lagged order flow, Δx_{t-1}, captures the anticipation effect, which implies that order flow precedes the exchange rate, either because the currency price does not adjust before news anticipated by order flow, or the order flow itself, is observed by the public. The lagged price change, Δp_{t-1}, captures the feedback effect, which suggests that order flow lags price due to feedback trading.

Table 25 presents the results. It reveals significant, negative feedback trading for all currency pairs during the day and night, and in the evening for the USD/GBP. This indicates that a negative return in period t (e.g. at daytime) is preceded by a positive return in period t-1 (e.g. at night).

All currency pairs exhibit highly significant and negative coefficients on the lagged order flow: the USD/GBP and the EUR/NOK at daytime, and the USD/ZAR in the evening. In the case of the EUR/NOK, this indicates that if order flow is positive at night, the Norwegian krone is expected to strengthen compared to the euro the following day (EUR/NOK decreases). This implies that the immediate depreciation of the NOK relative to the EUR during the night caused by the positive order flow (net selling pressure of NOK), is partially reversed at daytime. This shows that a portion of the exchange rate movement during the night is just noise, and is corrected the following day.

It is also worth noticing that including anticipation and feedback effects increase the explanatory power relative to a model with only order flow as independent variable.

Table 25: Feedback and Anticipation Effects

	Const. (a)	Δx_t (b)	Δx_{t-1} (b)	Δp_{t-1} (d)	R^2 (e)	White (f)	ARCH (g)	B-G (h)
EUR/NOK								
Day	0.002	0.222***	-0.017**	-0.145*	0.262	0.00	0.00	0.01
	(0.30)	(26.919)	(-2.013)	(-1.811)	0.262		0.00	0.00
Evening	0.011***	0.074***	-0.004	-0.016	0.241	0.00	0.00	0.00
	(5.22)	(18.542)	(-1.318)	(-1.634)	0.241		0.00	0.03
Night	0.009***	0.065***	0.002	-0.276***	0.317	0.00	0.00	0.05
	(4.21)	(18.527)	(0.722)	(-8.435)	0.317		0.47	1.00
USD/GBP								
Day	0.033***	0.309***	-0.031***	-0.193***	0.384	0.00	0.00	0.00
	(4.89)	(33.823)	(-3.700)	(-3.006)	0.384		0.00	0.00
Evening	0.002	0.103***	-0.004	-0.035***	0.298	0.00	0.00	0.66
	(0.55)	(13.651)	(-0.947)	(-3.279)	0.298		0.01	0.53
Night	-0.010***	0.118***	-0.002	-0.065***	0.419	0.00	0.00	0.93
	(-4.08)	(28.782)	(-0.402)	(-2.859)	0.419		0.00	1.00
USD/ZAR								
Day	-0.176***	0.512***	-0.013	-0.409***	0.319	0.00	0.00	0.46
	(-12.51)	(28.933)	(-0.356)	(-2.677)	0.318		0.00	0.00
Evening	0.015**	0.255***	-0.022**	0.003	0.333	0.00	0.00	0.00
	(2.32)	(13.983)	(-2.182)	(0.159)	0.332		0.00	0.00
Night	-0.010	0.218***	0.008	-0.184**	0.255	0.02	0.21	0.02
	(-1.35)	(20.741)	(0.504)	(-2.289)	0.255		0.00	1.00

Note: Specification (a) is the constant term. (b) is the intradaily order flow between time t-1 and t. (c) is the lagged order flow. The coefficients on order flow and lagged order flow measure the impact of a one-standard deviation change in order flow. (d) is the lagged price change. T-statistics are shown in parentheses. Specification (e) shows the R^2 and the adjusted R^2. (f) and (g) present the p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (h), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

5.2.5 Order Flow Impact during the World Financial Crisis

The graphs of order flow and trading volume (figure 2 and 4) reveal signs of increased activity during the financial crisis. Yet, this does not necessarily indicate higher liquidity. Participants in the market commonly regard the foreign exchange market, due to its size, as highly liquid at all times. However, Mancini, Ranaldo, and Wrampelmeyer (2013) have documented significant declines in liquidity during the financial crisis. In addition, the graphs of bid-ask spreads (figure 5) reveal peaks in late-2008. Another approach to analyse how the liquidity in the market affects order flow´s impact on exchange rates, is thereby to investigate order flow impact during the world financial crisis in 2007-2009.

The sample is split into three sub-samples: Before the world financial crisis (from 1999 to mid-2007), during the world financial crisis (from mid-2007 to mid-2009), and after the financial crisis (mid-2009 to 2015). Table 26 presents order flow coefficients and shows that they are larger during the world financial crisis, indicating that order flow had larger impact on exchange rates during the world financial crisis than in the period before and after. The explanatory power of order flow is also higher during the world financial crisis.

When comparing the order flow coefficient with the normal standard deviation of exchange rate returns in the sub-samples (table C, appendix), the results persist. Although standard deviations are higher during the financial crisis, the ratio of order flow impact to standard deviation is also higher than in the period before and after, indicating higher order flow impact during the financial crisis. This implies that order flow´s impact on prices is higher in less liquid periods.

Table 26: Order Flow Coefficients Sub-Sample

	USD/GBP	EUR/NOK	USD/ZAR
01.01.99-31.07.07	0.26	0.21	0.57
	(22.89)	(28.10)	(18.19)
	0.329	*0.383*	*0.344*
01.08.07-31.07.09	0.51	0.41	0.86
	(17.98)	(14.46)	(14.57)
	0.465	*0.446*	*0.422*
01.08.09-01.12.15	0.27	0.16	0.39
	(27.17)	(14.63)	(19.26)
	0.384	*0.121*	*0.257*

Note: Table 26 reports order flow coefficients when running regression 5.2.2 at daytime for different sub-samples, with t-statistics in parentheses and R^2 in curved. The order flow coefficients measure the impact of a one-standard deviation change in order flow. Standard errors are adjusted with the Newey-West procedure. All coefficients are significant at a 1 percent significance level.

5.2.6 Order Flow Impact on Holidays vs Normal Working Days

How the impact of order flow on exchange rates varies between normal working days and less liquid holidays is investigated by adding a dummy variable into the regression:

$$\Delta p_t = \alpha + \beta_1 H_t \Delta x_t + \beta_2 (1 - H_t) \Delta x_t + \varepsilon_t \qquad \text{(eq. 5.2.4)}$$

Here, H_t is a dummy variable that takes the value 0 if it is a normal working day, and the value 1 if it is a holiday. An overview of the holidays considered in the analysis can be found in table D in the appendix. Table 27 reveals non-significance of the dummy variable, indicating no significant difference on the impact of order flow between normal working days and holidays. I am thereby not able to conclude that order flow impact differs due to fluctuating liquidity from this analysis.

Table 27: Regression Result with Holiday Dummy Variable

	USD/GBP	EUR/NOK	USD/ZAR
Const.	0.07***	-0.02***	-0.19***
(a)	(7.33)	(-2.96)	(-11.28)
$H_t \Delta x_t$	0.90	0.26	0.17
(b)	(0.70)	(1.14)	(0.48)
$(1 - H_t)\Delta x_t$	0.37***	0.26***	0.57***
(c)	(27.94)	(28.47)	(23.85)
R^2	0.365	0.328	0.274
(d)	0.364	0.327	0.274
White	0.00	0.00	0.00
(e)			
ARCH	0.00	0.00	0.00
(f)	0.00	0.00	0.00
B-G	0.06	0.15	0.63
(g)	0.94	1.00	1.00

Note: Specification (a) is the constant term. (b) measures the order flow impact on holidays. The order flow coefficients measure the impact of a one-standard deviation change in order flow. (c) measures the order flow impact on normal working days. H_t is the holiday dummy variable with value 0 if it is a normal working day and 1 if it is a holiday. T-statistics are shown in parentheses. Specification (d) shows the R^2 and the adjusted R^2. (e) and (f) present the p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (g), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

5.2.7 Discussion

It is clear from the regression results that the variation in order flow´s impact on exchange rates throughout the day is highly statistically significant for all currency pairs. Order flow seems at first sight to have approximately three times higher impact on exchange rates at daytime than in the evening and at night. Order flow also had up to twice as much impact on exchange rate returns during the world financial crisis. There is no evidence that order flow has varying impact on returns on holidays and at normal working days.

However, when looking at the economic significance of order flow, the results are not that convincing. By comparing the order flow coefficient with the normal standard deviation of exchange rate returns, order flow impact does not distinguish a clear pattern throughout the day. The large order flow coefficients at daytime seem to be just a result of higher standard deviations at daytime. From these results, it is thereby not possible to conclude that order flow impact varies between highly liquid and less liquid periods of the day. In addition, it is found that some of the order flow impact at night is simply removed the following day for the EUR/NOK and the USD/GBP, indicating that a portion of the price movements at night is just noise.

When evaluating order flow coefficients during the world financial crisis relative to the standard deviation of exchange rate returns for the same period, the results displaying higher order flow impact during the financial crisis seem to persist. The ratio of order flow impact to standard deviation is higher during the crisis than before and after. It is therefore safe to conclude from this analysis that order flow affected prices more in the less liquid period of the financial crisis, in line with economic theory.

6. Conclusion

This paper generally investigates the relationship between order flow and price movements in the FX market, and specifically how this relationship varies during the day. The analysis is thereby split into two parts. The first part looks at the explanatory power of order flow on exchange rate returns, and the second part investigates how this varies on an intraday level. The study is extended by looking at order flow impact during the world financial crisis and on holidays. The analysis is performed for three currency pairs, EUR/NOK, USD/GBP, and USD/ZAR, for the period 1999-2015.

In the first part, the simple macro model provides poor results. When including order flow the explanatory power increases tremendously. It yields R^2 of 34 percent (EUR/NOK), 33 percent (USD/ZAR), and 38 percent (USD/GBP), compared to maximum 11.9 percent for the traditional macro model. This indicates that if there is a large buying pressure in the market and the volume of currency bought is higher than that of the currency sold, this will lead to the currency in question appreciating, which is in line with economic theory. The result strongly demonstrates that an increase in net buying pressure leads to higher prices, and that order flow is a significant determinant of exchange rates, in accordance with previous research.

Following the macro approach, order flow should not matter for exchange rate determination. However, the fact that order flow seems to explain a high variation of exchange rate returns does not exclude macro fundamentals from being the underlying determinant. Order flow may simply be a better "proxy" for these underlying fundamentals.

The overall results obtained in the first part of this paper seem to emphasize the role played by order flow in the foreign exchange markets. It has provided evidence that order flow is highly important when attempting to explain variations in exchange rates, and it gives important insight into some of the puzzling exchange rate questions that have been raised.

In the second part of the thesis, I compare periods with low trading activity with active trading periods to provide insight into how the liquidity of the FX market affects prices. The regression results reveal a highly statistical significance in the variation in order flow´s impact on exchange rates throughout the day. However, when looking at the economic significance, by comparing order flow coefficients with the normal standard deviations of exchange rate returns, the results are less convincing. I find no clear pattern in the order flow impact throughout the day, indicating that I cannot conclude that the relationship between order flow and price movements varies between day and night. There is no evidence that price-relevant information and expectations affect exchange rates more in periods with lower liquidity, as would be expected.

To be able to capture important dynamic structures in the exchange rate and further investigate the order flow impact, the analysis was extended by adding lags of the explanatory and explained variables. The EUR/NOK and the USD/GBP exhibit highly significant and negative coefficients on the lagged order flow at daytime. In other words, some of the order flow impact during the night is reversed the upcoming day. This indicates that a portion of price movements at night is just noise and will be corrected the following day.

Another approach used to study how the liquidity in the market affects order flow´s impact on exchange rates, was to investigate order flow impact during the world financial crisis in 2007-2009. The analysis reveals statistical and economic significance for the greater order flow impact on exchange rate returns during the world financial crisis, compared to the period before and after. This result is in accordance with economic theory, which states that prices tend to move more abruptly and in larger increments in less liquid markets.

When testing how the relationship between order flow and returns varies between normal working days and holidays, no significant difference is found.

Altogether, the study shows conflicting results. When investigating the relationship throughout the day, I find statistical, but not economic significance of the varying order flow impact between liquid and less liquid periods. When evaluating normal working days and holidays, no significant difference is found. When looking at the world financial crisis, I find evidence that order flow has greater price impact in periods characterized by low liquidity. It is thereby not possible to draw a robust conclusion on how buying pressure affects prices in the FX market. Clearly, this area of research needs further investigation.

7. References

Bień-Barkowska, K. (2011). "Multistate Asymmetric ACD Model: An Application to Order Dynamics in the EUR/PLN Spot Market." *National Bank of Poland Working Paper No. 104*. National Bank of Poland, Economic Institute.

BIS. (2016). *Triennial Central Bank Survey of Foreign Exchange and OTC Derivatives Markets in 2016.* Bank for International Settlements. URL: https://www.bis.org/publ/rpfx16.htm.

Breedon, F. & Ranaldo, A. (2013). "Intraday patterns in FX returns and order flow." *Journal of Money, Credit and Banking, 45*(5), 953-965.

Engel, C. (1996). "The forward discount anomaly and the risk premium: A survey of recent evidence." *Journal of Empirical Finance, 3*, 123-192.

Evans, M.D.D. & Lyons, R.K. (1999). "Order flow and exchange rate dynamics." National Bureau of Economic Research.

Evans, M.D.D. & Lyons, R.K. (2002). "Order flow and exchange rate dynamics." *Journal of Political Economy, 110*(1), 170-180.

Evans, M.D.D. & Lyons, R.K. (2006). "Understanding order flow." *International Journal of Finance and Economics, 11*(1), 3-23.

Evans, M.D.D. & Rime D. (2016). "Order flow information and spot rate dynamics." *Journal of International Money and Finance, 69,* 45-68.

Flood, R.P. & Rose, A.K. (1995). "Fixing exchange rates: a virtual quest for fundamentals." *Journal of Monetary Economics, 36,* 3-37.

French, K.R. & Roll, R. (1986). "Stock return variances: The arrival of information and the reaction of traders." *Journal of Financial Economics, 17*(1), 5-26.

Harris, M. & Raviv, A. (1993). "Differences in opinion make a horse race." *Review of Financial Studies*, *6*(3), 473-506.

Harvey, C.R. & Huang, R.D. (1991). "Volatility in the foreign currency futures market." *Review of Financial Studies, 4*(3), 543-569. doi: https://doi.org/10.1093/rfs/4.3.543

Hodrick, R.J. (1988.) "The empirical evidence on the efficiency of forward and futures foreign exchange markets." *Journal of International Economics, 25*(3-4), 387-390.

Ito, T. & Lin, W. (1992). "Lunch break and intraday volatility of stock returns: An hourly data analysis of Tokyo and New York stock markets." *Economics Letters, 39*(1), 85-90.

Jones, C.M., Kaul, G., & Lipson, M.L. (1994). "Information, trading, and volatility." *Journal of Financial Economics, 36*(1), 127-154.

King, M.R., Osler, C.L., & Rime, D. (2012). "Foreign exchange market structure, players and evolution." In James, Marsh and Sarno (Ed.), *Handbook of Exchange Rates.* Hoboken, NJ, USA: John Wiley & Sons, Inc.

Lyons, R.K. (1995). "Tests of microstructural hypotheses in the foreign exchange market." *Journal of Financial Economics, 39*(2-3), 321-351.

Lyons, R.K. (2006). *The microstructure approach to exchange rates.* MIT Press Books: The MIT Press.

Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). “Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums.” *Journal of Finance, 68*(5), 1805-1841.

Naranjo, A. & Nimalendran, M. (2000). “Government intervention and adverse selection costs in foreign exchange markets.” *Review of Financial Studies, 13*(2), 453-477.

Payne, R. (2003). “Informed trade in spot foreign exchange markets: An empirical investigation.” *Journal of International Economics,* 61(2), 307-329.

Sager, M. & Taylor, M.P. (2008). “Commercially available order flow data and exchange rate movements: Caveat Emptor.” *Journal of Money, Credit and Banking, 40*(4), 583-625.

8. Appendix

Table A: Unit Root Tests Transformed Series

Series	**EUR/NOK**		**USD/GBP**		**USD/ZAR**	
Test	**ADF**	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**
Null	*Unit root*	*No UR*	*Unit root*	*No UR*	*Unit root*	*No UR*
Spot	***		***		***	
Bid-ask spread	***		***		***	
Volume	***		***		***	
Interest rate diff.	***		***		***	

Test	**ADF**	**KPSS**
Null	*Unit root*	*No unit root*
Oil price	***	
VIX	***	
VXYG7	***	
VXYEM	***	

Note: Table A presents results of the ADF test and the KPSS test for the transformed series. The AFD has a null hypothesis of a unit root, and the KPSS test has a null hypothesis of no unit root. Asterisks *, **, *** denotes significance at the 10, 5 and 1 percent level respectively.

Table B: Robustness Check Regression 5.1.6

	EUR/NOK	USD/GBP	USD/ZAR
Const.	-0.019***	0.055***	-0.176***
(a)	(-2.90)	(6.22)	(-9.15)
Δx_t	0.24***	0.34***	0.50***
(b)	(23.50)	(27.98)	(19.82)
$\Delta(i_t - i_t^*)$	1x10^{-4}	-0.001*	-1x10^{-4}
(c)	(0.50)	(-1.72)	(-0.37)
$\Delta spread_t$	0.19***	0.045	0.20*
(d)	(4.35)	(0.39)	(1.71)
Δoil_t	-1.19***	-1.90***	-1.19
(e)	(-3.02)	(-3.99)	(-1.23)
ΔVIX_t	0.23	-0.07	0.23
(f)	(1.11)	(-0.40)	(0.55)
ΔVXYG7/ ΔVXYEM	1.26*	2.09**	10.10***
(g)	(1.77)	(2.39)	(5.48)
Δvol_t	0.022	2.09**	0.12**
(h)	(1.20)	(2.39)	(2.38)
R^2	0.348	0.381	0.328
(i)	0.348	0.380	0.327
White	0.00	0.00	0.00
(j)			
ARCH	0.00	0.13	0.00
(k)	0.00	0.15	0.00
B-G	0.11	0.11	0.24
(l)	0.13	1.00	0.60

Note: Table B presents results of running regression 5.1.6 without outliers for the interest rate differential. Observations on December 11th, 2003 and September 30th, 2008 are removed. Specification (a) is the constant term. (b) is the order flow between day t-1 and t. The coefficient measures the impact of a one-standard deviation change in order flow. (c) denotes the change in the one-day interest differential from day t-1 to t. (d) is the log daily change in the bid-ask spread. (e) denotes the log change in the oil price from day t-1 to t. (f) is the log change in the VIX from day t-1 to t. (g) is the log change in the VXYG7 (for the EUR/NOK and USD/GBO)/VXYEM (for the USD/ZAR) from day t-1 to t. (h) is the log daily change in the trading volume. T-statistics are shown in parentheses. Specification (i) shows the R^2 and the adjusted R^2. (j) and (k) present the p-values of the White test and the ARCH test for heteroscedasticity, with first-order and fifth-order in the top and bottom row, respectively. The p-values of the Breusch-Godfrey LM test for autocorrelation are reported in (l), with first-order and fifth-order in the top and bottom row, respectively. Standard errors are adjusted with the Newey-West procedure. Asterisks *, **, *** denote significance at the 10, 5 and 1 percent level respectively.

Table C: Standard Deviation of Exchange Rate Returns in Sub-Samples

	USD/GBP	EUR/NOK	USD/ZAR
01.01.99-31.07.07	0.46	0.34	1.02
01.08.07-31.07.09	0.75	0.61	1.29
01.08.09-01.12.15	0.44	0.49	0.79

Note: Table C presents daily standard deviations of exchange rate returns during three different sub-samples: before the world financial crisis, during the world financial crisis, and after the world financial crisis.

Table D: Holidays Used for Holiday Dummy Variable

EUR/NOK	USD/GBP	USD/ZAR
January 01: New Year´s Day	January 01: New Year´s Day	January 01: New Year´s Day
Maundy Thursday	January 02: New Year´s Day Holiday	January 02: Public holiday
Good Friday	Good Friday	April 27: Freedom Day
Easter Monday	Easter Monday	May 01: Workers Day
May 01: Labor Day	May Day Bank Holiday	June 16: Youth Day
May 17: Constitution Day	Spring Bank Holiday/Memorial Day	July 04: Independence Day
Ascension Day	July 04: Independence Day	August 09: National Women´s Day
Whit Monday	Labor Day	September 24: Heritage Day
December 25: Christmas Day	Thanksgiving	December 16: Day of Reconciliation
December 26: St. Stephen´s Day	Day after Thanksgiving	December 25: Christmas Day
	December 25: Christmas Day	December 26: Day of Goodwill
	December 26: Boxing Day	

Note: Table C presents the holidays used for the holiday dummy variable in section 5.2.6.

ID number: **0945860**

Preliminary Master Thesis Report

How does order flow affect exchange rates in the FX market?

Supervisor:
Dagfinn Rime

Hand-in date:
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Campus:
BI Oslo

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GRA 19502 Master Thesis

Programme:
Master of Science in Business, Finance

Table of Content

1. Introduction

The foreign exchange (FX) market is the largest financial market in the world with a daily turnover of $5.1 trillion as of April 2016 (B.I.S., 2016). The FX market has gone through significant changes over the past couples of decades. Before the 1990s, limited competition, high entry barriers and high spreads characterized it. The market was mainly broker-dealer driven. The introduction of electronic brokering in the 1990s changed the nature of the market. Increased transparency, reduced transaction costs and new customer classes now characterized the FX market (NASDAQ, 2017).

Harvey and Huang (1991) remark several characteristics of the FX market that distinguish it from other financial markets. The trading is primarily over-the-counter, and major traders are foreign exchange brokers and banks. The emergence of electronic trading and globalization have contributed to high volume, twenty-four hour trading. These features make the market highly liquid, and as a result, the FX market is believed to be the most efficient financial market. These characteristics make the FX market strikingly interesting, and the determination of exchange rates has sparked a lively debate within the academic profession.

The classical models of macroeconomic theory states that exchange rates are determined by a set of macroeconomic variables, such as GDP growth, interest rates, money supply and inflation among others. The models of uncovered interest rate parity (UIP) and purchasing power parity (PPP) model were helpful for explaining exchange rate movements in the long run, but did not provide explanations for short-run movements. Because of such disappointing empirical results a new field of study emerged: the theory of microstructure. This theory assumes that market participants have heterogeneous expectations, and thereby the structure of the market itself might influence exchange rate determination.

One very important determinant in the field of microstructure finance is order flow. Order flow is defined as the net of buyer-initiated and seller-initiated orders, and is thereby a measure of net buying pressure (Evans and Lyons, 2002). The reason for its importance is that order flow conveys information. Several studies have found evidence for a strongly positive correlation between order flow and nominal exchange rates, indicating that price increases with buying pressure. This represents a radical shift from traditional macro-models, which state that actual trades are neither necessary nor sufficient for price movements.

1.1 Research Question

The main objective of this study is to investigate the formation of prices in the foreign exchange market. Main determinants for prices are information and participants' expectations of the future. One way to interpret how the information processing takes place is to compare times with large trading volume with times where almost no active trading takes place. This will give us insight into whether the processing of information is connected with the actual trading going on in the market at that time, and if the trading volume affects participants' actions and expectations. This thesis will therefore investigate how the price determination, the relationship between prices and order flow, varies between day-time and night-time, and between normal working days and holidays. The main goal is to investigate if information flows similarly at periods with low trading as in active trading periods.

Order flow is by many microstructure researchers seen as a significant determinant of exchange rates and can also be used to forecast exchange rates out of sample (Evans and Lyons, 2002). However, Sager and Taylor (2008) find little empirical evidence supporting these conclusions. This thesis will investigate determinants of exchange rate movements using high-frequency data over the period 1999 to 2015. It will focus specifically on the relationship between price movements and order flow. In addition, it will investigate this relationship in the light of several state parameters: volume, bid-ask spread, number of quotes and standard deviation. The research question is specified as:

"How does order flow affect exchange rates in the foreign exchange market?"

1.2 Contribution and Motivation

This analysis is important in a general manner because it can contribute to answering some of the deepest and most important issues in finance: how prices are determined. Because of the characteristics of the foreign exchange market, determination of exchange rates, which are after all just prices, is even more complex than in other financial markets. In the literature, there is no single theory fully explaining the exchange rate determination. More specifically this study can help to explain the impact of order flow on prices in the FX market, and how this is related to other factors like volume, bid-ask spreads etc. This is important to all market participants and other relevant actors making investment decisions and trying to understand the FX market. The overall motivation for the study is therefore that it hopefully can contribute, if only a tiny bit, to enhance the understanding of unsolved exchange rate puzzles.

2. Theory and Literature Review

2.1 Macro Models

The early macro models of floating exchange rates were designed inductively due to the absence of historical experience. These standard models of exchange rates are based on the view that only common knowledge macroeconomic information matters. They are built on macroeconomic variables such as interest rates, GDP growth, price levels, inflation etc. Uncovered interest rate parity (UIP) and purchasing power parity (PPP) states that the exchange rate is supposed to balance the relative price levels and interest rates in two countries, and are well-established models in macroeconomic theory.

In the 1990s, these macro models showed disappointing empirical performance. In research conducted by Hodrick (1987) and Engel (1996), UIP and PPP both failed to hold at short horizons. The PPP model is helpful in explaining long-run exchange rate movements, but provides little explanation for movements in the exchange rate in the short-run. Evans and Lyons (2002) analysed real world data and found that the R^2 of models based on macroeconomic fundamentals rarely exceeds 10%, and forecasts based on them are not better than random walk simulations, they are actually performing worse. These models also fail to predict the direction of the exchange rate change, and are thereby defeated by a simple "no change" framework.

2.2 Microstructure

In light of these failures, a microeconomic approach to understand the determination of exchange rates emerged in the 1990s. Researchers have proposed that the massive trading volume in the FX market is the reason why the fundamental approach fails. Trading activity has no role in regards to macroeconomic variables when determining the exchange rate, thereby the traditional models do not account for trading volume. The microstructure approach was designed deductively, and focuses on how the structure of the market itself might influence exchange rate determination. It is based on the assumption that different market participants may have asymmetric information concerning the state of the macro economy and differ in their motives for trading currencies, thereby emphasizing that heterogeneous beliefs are essential to determine prices (Evans and Rime, 2016).

French and Roll's paper from 1986 discusses how the volatility of equity returns differs during the day. They found especially that prices are more variable during exchange trading hours than during non-trading hours. They provide three possible explanations for this to happen. The first is that more public information arrives during normal business hours, because it is a by-product of normal business activities. Public information is by definition incorporated into stock prices at the moment it is known; thereby the return variance for a business day should not depend on whether the exchanges are open or closed. The second plausible explanation is that private information only affects prices through trading, and informed investors are likely to trade when the exchanges are open. This means that most private information is incorporated into prices during trading hours, which creates higher variance when the exchange is open. The last alternative is that the process of trading itself introduces noise into stock returns. Their conclusion was that only 4-12% of the daily variance is caused by mispricing. The main reason for varying volatility is differences in the flow of information during trading and non-trading hours, and most of this information is private.

Jones et al (1994) evaluate the flows of public and private information and their relation to short-run volatility. Here, non-trading periods are defined as periods when exchanges are open, but traders endogenously choose not to trade. They find a substantial proportion of daily stock return volatility to occur without trading, and that public information also might lead to trading. Harris and Raviv (1993) find that public information may be the major determinant of short-run volatility. They also state that even without any private information, and therefore without any information asymmetry, trading can occur due to differences in opinion.

Macroeconomic theory generally assumes that agents are symmetrically heterogeneous, which means they differ, but in the same way. In contrast, traders in the FX market can be categorized into different groups depending on their motivation, their attitude towards risk, and their horizons (Evans and Lyons, 2006). Some agent types do not exhibit the behaviour of agents in the standard models. Retail investors for instance, do not conform to the standard view that all agents are perfectly rational (Heimer and Simon, 2011). The microstructure view is based on the assumption that heterogeneous beliefs are essential to determine prices.

2.3 Order Flow

Evans and Lyons have through several papers reported results that strongly support the microstructure view on exchange rates. In 1999 they use a model that includes interest rates differential and order flow that is able to explain 60% of the variation in daily exchange rates of DEM/USD, it thereby performs much better than the macroeconomic models. Evans and Lyons (2002) present a new class of models that highlight new variables that macro models ignore, with order flow as the most important one. They regress the base currency's daily return on order flow and fundamentals. The explanatory power of these regressions is 40-60%, which beats the regressions on fundamentals alone by far. They predict that macroeconomic information impact on exchange rates both directly and indirectly via order flow. The common knowledge part of news directly affects the exchange rate by shifting the equilibrium price, while order flow reflects heterogeneous interpretations of these news for the new equilibrium price.

Order flow and nominal exchange rates are strongly positively correlated. Lyons (1995), Payne (1999) and Naranjo and Nimalendran (2000) among others, have proved that foreign exchange order flow conveys information. Microstructure theory emphasized that different agents may have distinct information concerning the state of the macro economy. Order flow enables market makers to aggregate changes in expectations about the state of the economy. Thereby, order flow affects exchange rates because they contain price-relevant information to market participants.

Bień-Barkowska (2011) finds the intraday foreign exchange rate's sensitivity to changes in order flow to be significantly larger in the morning, afternoon and in periods where there are more premises for informed trading. Breedon and Ranaldo (2013) investigate the relationship between exchange rates and order flow closer. In their model returns are a function of current order flow, lagged order flow and lagged returns. They find that the daily pattern order flow, which is a result of different time zones, seems to sufficiently explain the exchange rates' daily seasonality. Lyons (2006) presents two channels through which order flow might affect exchange rates. Order flow might create imbalances in certain dealers' inventory. An inventory-control channel appears when dealers adjust prices to control their inventory fluctuations. An information asymmetry channel emerges when dealers adjust prices in response to costumer trades that may contain private information. These two channels are helpful in illustrating why the varying order flow could cause intraday seasonality in exchange rates.

Further, Evans and Rime (2016) report that order flow has significant forecasting power for future depreciation rates over much longer time periods than what has earlier been reported. However, they found that order flow's forecasting power arises because flows carry information concerning future risk premium, not information about future interest differentials. They also revealed that the information conveyed by order flows concerning risk premium significantly affected the behaviour of the EUR/NOK exchange rate in several period around the world financial crisis and European debt crisis.

However, several researchers have found lack of empirical evidence supporting the conclusion that order flow is the significant determinant of exchange rates. Sager and Taylor (2008), using both interdealer and commercially available customer order flow data, found little evidence that order flow could predict exchange rate movements out of sample. In addition, they found a Granger-causal relationship running from exchange rate returns to customer order flow.

3. Data

The high-frequency exchange rate data on prices and order flow to be used in this analysis, including data on state parameters like volume, bid-ask spread, number of quotes and standard deviation, will be provided by professor Dagfinn Rime. The dataset will consist of daily data from 1999 to 2015, and each day will have two data points, one at 07:00 GMT and one at 20:00 GMT.

Although the FX market is open twenty-four hours a day, not much trading occurs between 20:00 GMT and 07:00 GMT, which we define as "night". Between 07:00 GMT and 20:00 GMT is thereby defined as "day". By looking at currency pairs within more or less the same time zone, we avoid the problem of varying "active trading hours" among the currencies, which would make the analysis more complex. The following currencies will be investigated: the Norwegian krone (NOK), the UK sterling (GBP), the Euro (EUR) and the South African rand (ZAR). The selection is based on the currencies that have the highest trading volume within the relevant time zone: the UK sterling and the Euro. The analysis will include the Norwegian krone as this is of specific interest to the researcher. The South African rand is added to include an example of an emerging market in the analysis.

Further information and details on data will be provided in the final thesis.

4. Methodology

In order to investigate how order flow affects prices/exchange rates in the foreign exchange market, we will run several regressions for each currency pair with the exchange rate as the dependent variable and order flow as the independent variable. Exactly how this will be done is not yet decided, but several options are available. We can for instance run the following regression:

$$p_{20} - p_{07} = \alpha + \beta OF_{20} + \varepsilon$$

Where p_{20} is the exchange rate at 20:00 GMT, p_{07} is the exchange rate at 07:00 GMT, and OF_{20} is the order flow from 07:00 to 20:00 GMT, thus the order flow at day-time. This will reflect the relationship between prices and order flow at day-time. Then we will run a similar regression for night-time:

$$p_{07} - p_{20} = \alpha + \beta OF_{07} + \varepsilon$$

Where OF_{20} is the order flow from 20:00 to 07:00 GMT, thus the order flow at night-time.

After running these regressions, we will compare the betas. If they are significantly different, the relationship between order flow and prices are different at night compared to during the day.

Another alternative is to run the following regression:

$$\Delta p_{20} = \alpha + \beta_1 OF_{20} + \beta_2 OF_{07} + \varepsilon$$

Where Δp_{20} is the change in price from 20:00 GMT one day to 20:00 GMT the next day, and OF_{20} and OF_{07} are as explained above. Here, we will also compare β_1 and β_2 to investigate the relationship between prices and order flow.

A similar approach will be used to compare holidays and normal working days.

To inspect how the state parameters affect this relationship they will be added into the regression as dummy variables. Exactly how this is done will be determined during the regression process.

It is also an opportunity to split the sample into several sub-samples to look at characteristics during specific period, such as the financial crisis and European debt crisis.

5. Thesis Progression Plan

Time period	**Specification**
Jan 16th	Hand in Preliminary Master Thesis Report
Jan 16th - Mar 1st	Learn Eviews, collect and process data and produce descriptive statistics
Mar 2nd - Apr 15th	Analysis testing and interpretation of results
Apr 16th - May 31st	Write a draft of the thesis
Jun 1st - Jun 30th	Complete and hand in final thesis

6. References

Bień-Barkowska, K. 2011. “Multistate asymmetric ACD model: an application to order dynamics in the EUR/PLN spot market.” *National Bank of Poland Working Papers* 104, National Bank of Poland, Economic Institute

B.I.S. 2016. “Triennial Central Bank Survey: Foreign exchange turnover in April 2016.” Bank for International Settlement

Breedon, F. and Ranaldo, A. 2013. “Intraday patterns in FX returns and order flow.” *Journal of Money, Credit and Banking* 45 (5): 953-965

Evans, M.D.D. and Lyons, R.K. 2002a. “Informational integration and FX trading.” *Journal of International Money and Finance* 21 (6): 807-831

Engel, C. 1996. “The forward discount anomaly and the risk premium: A survey of recent evidence.” *Journal of Empirical Finance* 3: 123-192

Evans, M.D.D. and Lyons, R.K. 1999. “Order flow and exchange rate dynamics.” mimeo, Berkeley: Haas School of Business

Evans, M.D.D. and Lyons, R.K. 2002b. “Order flow and exchange rate dynamics.” *Journal of Political Economy* 110 (1): 170-180

Evans, M.D.D. and Lyons, R.K. 2006. “Understanding order flow.” *International Journal of Finance and Economics* 11 (1): 3-23

Evans, M.D.D. and Rime D. 2016. “Order flow information and spot rate dynamics.” *Journal of International Money and Finance* 69: 45-68

French, K.R. and Roll, R. 1986. “Stock return variances: The arrival of information and the reaction of traders.” *Journal of Financial Economics* 17: 5-26

Harris, M. and Raviv, A. 1993. “Differences in opinion make a horse race.” *Review of Financial Studies*, 6 (3): 473-506

Harvey, C.R. and Huang, R.D. 1991. “Volatility in the foreign currency futures market.” *Review of Financial Studies* 4: 543-569

Heimer, R.Z. and Simon, D. 2011. “Facebook finance: how social interaction propagates active investing.” Working Paper, Brandeis Univ. Int. Bus. Schl.

Hodrick, R.J. 1987. “The empirical evidence on the efficiency of forward and futures foreign exchange markets.” Chur: Harwood Academic Publishers

Jones, C.M., Kaul, G. and Lipson, M.L. 1994. “Information, trading, and volatility.” *Journal of Financial Economics* 36 (1): 127-154

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

Lyons, R.K. 2006. *The microstructure approach to exchange rates.* MIT Press Books: The MIT Press

Naranjo, A. and Nimalendran, M. 2000. “Government intervention and adverse selection costs in foreign exchange markets.” *Review of Financial Studies* 13 (2): 453-477

NASDAQ. 2017. “History of the foreign exchange (forex) market”. Accessed January 09, 2017. http://www.nasdaq.com/forex/education/history-of-retail-forex-market.aspx.

Payne, R. 1999. “Informed trade in spot foreign exchange markets: An empirical investigation.” Manuscript, London School Econ.

Roll, R. and Solnik, B. 1977. “A pure foreign exchange asset pricing model.” *Journal of International Economics* 7: 161-179

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