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An investigation of customer order flow in the Norwegian foreign exchange market

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Abstract

This thesis aimes at examining customer order flow in the Norwegian currency market (NOK/EUR). The key findings suggest heterogeneity among market participants, where non–financial customers' order flow is the primary information source that drives price movements and foreign banks' transaction flow provide liquidity in the market. However, the segments' effect on price is non-permanent. Further evidence indicates that the transaction flow is complimentary to the traditional fundamentals when modeling the exchange rate. The out of sample findings indicate that order flow based models perform better than a random walk and a traditional model for statistical forecasts.

Keywords: Microstructure approach, Customer order flow, Liquidity effect, Information effect

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1. Introduction

In a theoretical world where macroeconomic models have failed to explain more than 10 percent of the exchange rate movements (Evans and Lyons 2002) and forecast the exchange rate dynamics better than a random walk on a short horizon (Messe and Rogoff 1983; Cheung et al. 2005), the result of Evans and Lyons (2002) brought on new motivation. The authors gave evidence that order flow can explain 60 percent of MARK/USD movements and forecast the exchange rate significantly better than a random walk. This empirical result drew a bigger interest to the use the microstructure approaches to exchange rates, where the new determinant, order flow (signed transaction volume), plays the main role (Lyons 2001b).

This thesis outlines two prominent coexisting hypotheses from the broader microstructure literature to explain the order flow's relation to exchange rates, namely the liquidity effect and the information effect. *The information effect* has its origin in classical microstructure models such as Kyle (1985), which highlight the asymmetric information among market agents. The dealers extract non – public information by observing customers transactions in the FX market, which is converted into price change. Thus, customer order flow can be a source of information. *The liquidity effect* arises from the price elasticity of finite supply and demand (Shleifer 1986), and emerges in the FX market since individual dealers close out their position in the end of the trading day and need to induce customers to hold their position overnight by adjusting the risk premium. Thus, in order for a group of customers to change their net position, another group of customers has to absorb the dealer's inventory imbalance (Osler and Wang 2012; Gereben et al. 2006).

The main focus of this thesis is to examine the customer order flow in the Norwegian kroners market (NOK/EUR), by answering five central questions: First, does customer order flow have a permanent effect on the NOK/EUR exchange rate? Second, which segments' order flow contain price relevant information? Third, which typical market role do the customer types play in the Norwegian currency market? Fourth, does customer order flow add value to the traditional macro fundamental model? Fifth, can customer order flow help forecasting future exchange rates?

The thesis is structured as following. In section 2, a literature review summarizes earlier empirical findings relevant for the information and liquidity effect. Section 3 outlines the data and methodology. Section 4 presents the empirical results, which includes in sample and out of sample analysis. Section 5 concludes.

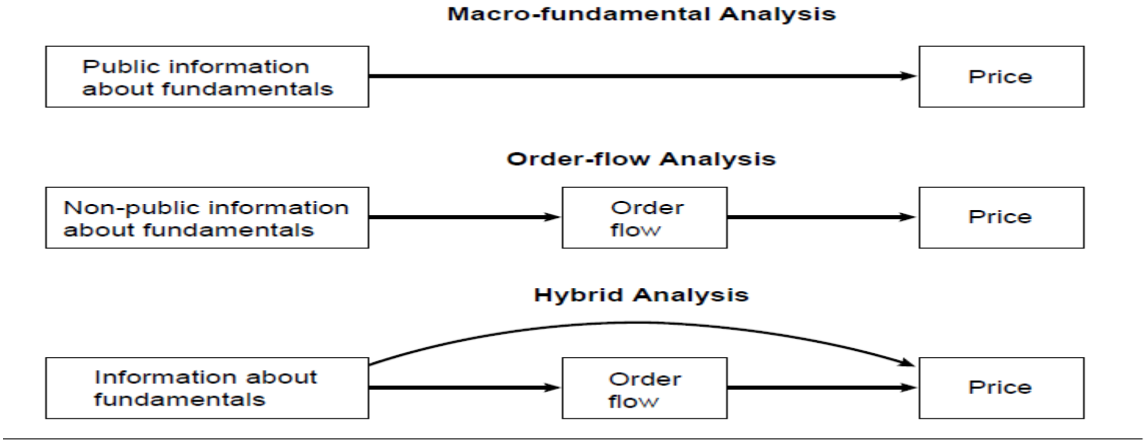
2. Literature review

This section reviews the most relevant empirical findings about the liquidity and information effect, where the latter hypothesis is emphasized in this dissertation.

2.1 The information effect

The microstructure approach originated from the field of microstructure finance, which emphasizes the order flow's role to convey information into the price. This is highly controversial for many economists, considering that macroeconomic models are based on the assumption that market participants share equal information and beliefs about the exchange rate, while the microstructure model identifies information heterogeneity among market participants when forming their price beliefs. This belief is measured in order flow, which can be defined as the market participants initiated purchase or sell trades, where an initiated purchase (sell) is signed as a positive (negative) order flow. Thus, the market makers can observe aggregated order flow to determine whether there is net purchase (selling) pressure in the FX market, which will cause an appreciation (depreciation) of a specific asset (Lyons 2001a).

Figure I. Macro – fundamental versus microstructure approach



Source: Lyons (2001b).

Figure I illustrates the different approaches. In a macroeconomic approach, fundamentals are assumed to have a direct and monumental impact on the price. However, in the microstructure approach the focus is on the agent's non – public information about fundamentals, which is conveyed into the price through the order flow. Dealers learn about fundamentals by observing the order flow and adjust the price accordingly. The hybrid approach combines the macroeconomic and the microstructure approaches, where information about fundamentals affect the price through both the direct and indirect channel, which is more similar to how price is determined in the actual market (Lyons 2001b). These links are empirically tested by Evens and Lyons (2008) who suggest that two thirds of the price impacts from macro news is transmitted by the order flow (indirect channel), while the remaining one third is impounded directly into the price (direct channel). Thus, the macro news are primarily impounded through the indirect channel, which is supported by the findings in Rime et al. (2010). These studies suggest the order flow function as a proxy for the underlying fundamental factors, which raises the next question: what kind of non-public or private information drives the order flow?

2.1.1 Private information

Microstructure research has identified different types of private information. In the empirical study by Evans and Lyons (2008) we saw that market participants had heterogeneous expectations about the macro news' impact on the price, which was primarily conveyed through the transaction flow. This indicates that the heterogeneous interpretations of macro news constitute a type of private information.

Private information can also emerge because of the delay between a macro variable realization in the economy and its public announcement (King et al. 2013). Evans and Lyons (2008) suggest that macroeconomic statistics are accumulated order flows released with lags, thus relevant information about macro fundamentals are dispersed between market participants. It can be argued that a bank with the lion share of the FX market has enough informative order flow to predict the state of the economy (Rime and Sojli 2006), which is exactly what the authors find evidence on. The results show that order flows can predict output growth, money growth and inflation significantly better than the exchange rate on a quarterly horizon based on 6.5 years of data from Citibank. Lyons and Evans' evidence is supported by Rime et al. (2010), confirming that order flows convey information about future macro statistical releases. Evans and Lyons (2002) reveal that order flows can contain private information about the discount rate, considering that dealers observe the necessary risk premium to create an equilibrium in the market.

It is evident that the order flow can convey private information about fundamentals, expectations on fundamentals and non–fundamental information, which brings us to the following question: who is informed?

2.1.2 End–user heterogeneity

Microstructure theory emphasizes end–user differentiation in terms of non–public information and motives to trade in the FX market. Fan and Lyons (2003) were the first to find evidence on heterogeneity among FX customers, which was further investigated in Evans and Lyons (2006). The authors used aggregated order flows (USD/EUR) from Citibank, which is broken into three main categories: short–term investments (hedge funds), longer–term investments (pension funds) and non–financial corporations. The customer segments differed in terms of statistical significance and effect. Non–financial customers had a negative effect on the price. Contrary, long-term investors (financial customers) had a positive price effect with the highest explanatory power across frequencies. Empirical studies support these findings by using different data sets and currency pairs (Bjønnes et al. 2005; Marsh and O'Rourke 2005; Osler and Vandrovych 2009; Menkhoff et al. 2012). The microstructure theory assumes that dealers gather information through observing customer trades. Nevertheless, a number of studies indicate that dealers also carry their own private information into the FX market. Osler and Vandrvych (2009) have evidence that dealer's transaction flow anticipate price better than six different customer segments' order flow (King et al. 2013).

Empirical studies strongly indicate that the order flow source is important, and the majority of studies suggest that financial customers are theoretically intuitive and better informed than other customer segments.

2.1.3 Forecasting

The empirical studies previously reviewed propose that order flows incorporate relevant information into the price. Based on that, a logical assumption would be that order flows can be used to forecast returns. Rime et al. (2010) found evidence that order flow can predict daily movements for three major currencies better than a random walk, and generate a sharpe ratio greater than one. Menkhoff et al. (2012) documented evidence on the order flow's ability to forecast 15 currency pairs by using daily-disaggregated customer order flow data for over a decade of time from UBS. There are also empirical studies indicating contrary results. Sager and Taylor (2008) study the commercial available order flow data from J.P Morgan, Reuters, and RBS. The result indicated that order flow had no significant predictive power on exchange rate movements for any horizon.

2.2 Liquidity effect

The liquidity effect can be explained through the context of Evans and Lyons (2002) three-round theoretical framework. In round one, customers trade with dealers to change their net position, which accumulate the dealers' inventory. These customers tend to drive the price change and move the market (Gereben et al. 2006), thus the round one customers' net transactions flow is anticipated to have a positive effect on the price. In round two, the dealers redistributes cumulated inventory with other dealers to share the risk. In round three, the dealers sufficiently adjust the risk premium to induce the customers to hold the dealers remaining inventory overnight to end the trading day with their preferred net zero position. This type of customers seek attractive opportunities in the FX market, which makes them sensitive to risk premium adjustment (Gereben et al. 2006). This implies that if dealers' increase (decrease) NOK/EUR, these customers will buy (sell) euro for kroners. Hence, the round three customers' net order flow is expected to have a negative effect on price. The bottom line is that, since dealers end the day with zero inventory, the round one customers demand for liquidity is ultimately provided by the round three customers (King et al. 2013). Bjønnes et al.'s (2005) findings show that financial customers' order flow has a positive price effect and that corporate customers' order flow has a negative price effect, with equal coefficient in terms of absolute value. In addition, the authors test for Granger casualty, which involves testing if one-time series can forecast another. The results indicate that financial customer order flow Granger-cause corporate order flow, and no casualty in the opposite direction. According to these results, the authors suggest that financial customers are typical round one customers and that corporate customers correspond to the typical third round customers, who provides overnight liquidity.

3. Data description and Methodology

3.1 Data description

This dissertation uses weekly nominal NOK/EUR exchange rates, disaggregated order flow, European crude oil price, EURIBOR 3M and NIBOR 3M with a sample period stretching from 3.10.05 to 13.11.16. For data with only daily observations available, weekly data has been created by taking the weekly average of daily observations using Excel.

Table I. Descriptive statistics of weekly interest rate, the exchange rate and the oil price

Data Sample	NOK/EUR	NIBOR 3M	EURIBOR 3M	European crude oil price
Mean	8.23	2.76	1.51	81.83
Maximum	9.84	7.72	5.38	141.07
Minimum	7.29	0.95	-0.31	27.76
Standard deviation	0.57	1.52	1.67	26.49

Note: The weekly data for NOK/EUR, interest rate and oil prices are edited daily data from 3.10. 05 to 13.11.16 with 580 observations. The NOK/EUR is data gathered from Norges Bank, European curde oil prices is provided by EIA, NIBOR 3M data is from Norges bank and Oslo Børs, and EURIBOR 3M is from Quandl..

3.1.1 Nominal exchange rate NOK/EUR

The nominal exchange rate NOK/EUR is provided by the central bank of Norway (Norges Bank), which gather daily observations for the currency pair. Table I shows that NOK/EUR currency on a weekly horizon has a mean of 8.23 with a minimum at 7.29 and a maximum of 9.84 and a standard deviation of 0.57. This indicates a high volatility of the exchange rate for the sample period considered.

3.1.2 3M NIBOR/EURIBOR

3 months NIBOR/EURIBOR is the interest rate used by banks when borrowing internally in the interbank market, where 3 months NIBOR is the interest rate between Norwegian banks, and 3 months EURIBOR is the interest rate between banks in the EU area. Hence, this interest rate should reflect the official bank rate with a risk premium. NIBOR 3M data sample is a

combination of daily data from Norges Bank (2005 – 2012) and Oslo Børs (2012 -2016). The EURIBOR 3M daily data sample is extracted from Quendl. Table I shows that the standard deviation for both interest rates for average weekly observations have a similar level.

3.1.3 Oil price

U.S Energy information administration provides daily data on European Brent spot prices in dollar per barrel. The descriptive statistics table indicates that the oil price is volatile with a mean of 81.83 and standard deviation of 26.49.

3.1.4 Order flow data

Table II. Descriptive statistics of weekly cumulative disaggregated order flow

	Reporting Banks	Foreign Banks	Financial customers	Non-Financial customers	Norges Bank	Aggregated order flow
Mean	-1.90	451.52	-20.08	276.14	-382.21	323.48
Standard deviation	8.25	225.44	15.03	142.20	158.72	195.07
Transaction volume (Bn.NOK)	27962.41	53623.91	11306.18	22342.86	793.89	116029.21
Transaction volume (%)	24%	46%	10%	19%	1%	100%

Note: Weekly disaggregated cumulative order flow data between 3.10.05 -13.11.16 with 580 observations. The transaction volume is absolute value of sales and purchases trades accumulated.

Norges Bank's statistics on foreign exchange transaction consist of reporting banks[1] foreign trades on currency pairs involving the Norwegian kroner, which cover 69 percent worldwide.[2] The Norges Bank has chosen to divide the counterparty of the trades in the following segments: reporting banks, foreign banks, financial customers, non – financial customers and Norges Bank.[3] The order flow data consist of spot and forwards transactions accumulated weekly, where 71 percent of the spot and one third of forwards trades involve the currency pair

[1] Nordic banks that quotes Norwegian kroners are obligated to report the amount of trades and the counterparty of the trade. An example could be a bank that buys one million euro with eight million kroners, will be reported as a negative order flow of eight million kroners in the statistics, considering that all transactions is counted in Norwegian kroners (SSB 2016)
[2] The data is limited considering that Norges bank started collection started in October 2005.
[3] **Financial clients** includes Norwegian banks (except reporting banks) and Norwegian financial clients. **Non-financial clients** includes Norwegian non-financial clients (excluding oil companies), foreign non-financial clients and oil companies.

NOK/EUR (Meyer and Skjelvik 2006). Order flow data is only available on a weekly horizon, considering that observations that are more frequent are confidentially reported to Norges Bank. Table II shows that order flow is volatile, when comparing standard deviations to the mean. The transaction volume varies according to segments, where foreign banks clearly have the largest transaction volume (46%) and financial customers have a relatively low trading volume (10%) compared to other papers in percentage of total volume (Fan and Lyons 2003; Evans and Lyons 2002, 2006; Lyons 2001[1]).

3.2 Methodology

Econometric methods bridge the gap between theory and empiricism, where econometric models are used to investigate if theory holds in reality. All the variables used for modelling are tested for non-stationarity using the augmented Dicker-Fuller method, to prevent spurious regressions. The rule that only stationary variables can be used in regression models has one exception, which involve co–integration between two or more variables in the model. The two-step Engle–Granger (EG) method is also applied to detect co-integration, where the residuals of two or more series are tested for non-stationarity to determine whether the time series follow the same trend in the long term. The ordinary least square (OLS) method is used to investigate the relationship between variables in sample. Out of sample, a recursive model is used for the one-step ahead forecast, where the dependent variable is explained by lagged values of explanatory variables. The forecasted value is determined by actual values for the lagged values, since the model re-estimates with new data for each prediction. The dynamic forecast (multiple-step ahead) is based on a vector autoregressive (VAR) model, where a dependent variable relies on historically realized values of itself and other independent variables. The model uses predicted values of the previous term to forecast the next period. Thus, the forecast is of higher uncertainty than a one–step ahead method, especially for a long prediction period. The Granger casualty method is applied to further examine if one-time series can forecast another. The idea behind Granger casualty is that if a variable X Granger–causes Y, then past values of X and Y together are superior at predicting Y than only past values of Y (Brooks 2008). The Toda and Yamamoto (1995) procedure is used to test for causality, and is based on a bivariate VAR model. This approach suggests using data series in levels even if the process indicates integration. The VAR is specified after the usual lag selection procedure, and then extra lags for the variables are added depending on the highest order of integration of the process.

4. Results

This section presents the empirical results in four parts, where the first part involves non-stationarity testing and co-integration detection. The second part investigates the relation between end-user flow and the exchange rate. The third part identifies market roles by examining customer segments relation to each other. The fourth part compares a hybrid model to a traditional model to assess the order flow ability to add value to macro fundamentals when modeling the exchange rate. The last part tests order flow-based models performance when forecasting return.

4.1 Pairwise co-integration

Table III. Summary of ADF-test

	NOK/EUR	3MInterest Differential	Oil price	Reporting banks	Foreign bank	Financial customer	Non-financial customer	Norges Bank
Level	-1.734	-2.116	-1.511	-0.974	-2.298	-1.716	-1.920	-2.208
1st Difference	-20.116*	-19.313*	-18.796*	-21.441*	-17.58*	-21.224*	-11.95*	-3.718*

Note: The table summarize the results from the ADF – test, where t – value have to be below critical value 1% (-3,443415), 5% (-2,867195), 10% (-2,569844) to reject the null hypothesis. * indicates stationarity level of confidence at 1%, ** at 5% and *** at 10%.

The data series are tested for non-stationarity with the use of the augmented Dicker–Fuller test (ADF) to prevent spurious regressions. The test rejects the null hypothesis that a data series has a unit root, when the t–statistics is below the critical values. Table III shows that the variables are not stationary in levels, but stationary in first difference at a 1% level of significance. This indicates that the series are valid for co-integration testing, which is conducted to examine the long-term relation between customer segments and the exchange rate (NOK/EUR). End-user flow that compound relevant information into the price is anticipated to co-integrate with price, considering that relevant price information is assumed to have a permanent effect (Rime 2001).

Table IV. Pairwise co–integration

	Reporting banks	Foreign banks	Financial customers	Non–financial customers	Norges Bank
ADF test	-1.75	-1.74	-1.702	-1.768	-1.70

Note: The table summarize result from two–step EG test. The ADF-test row presents the result in t–statistics, where significance on a 5% level is indicated by *(critical value: -3,364). The Estimate period is from 03/10/2005 to 07/11/2016 with 577 observations.

The results from table IV show that we cannot reject the null hypothesis that end-user flow has a unit root on a 5% significance level, which indicates no co-integration relationship between any of the end user's transaction flow and the exchange rate. This implies that the effect from customer order flow is transitory, which is surprising, considering that empirical studies in general suggest a permanent effect (Rime and Sojli 2006).

4.2 Customer order flow regression analysis

The order flow source is further investigated through testing the relation between the change in end-user transaction flows[4] separately against the dependent variable *Δlog(NOK/EUR),* and together in the customer order flow model[5] with the end–customer transaction flows as explanatory variables on a weekly horizon. The result is interpreted in terms of the information effect, before further analysis is conducted to identify the market roles in the next sub section.

[4] The difference of each segment cumulative order flow is the customer's net purchase on a weekly term.
[5] Customer order flow model: $\Delta log(NOK/EUR) = \beta 0 + \beta 1\Delta(Reporting\ banks) + \beta 2\Delta(Foreign\ banks) + \beta 3\Delta(Financial\ customers) + \beta 4\Delta(Non - financial\ customers) + \beta 5\Delta(Norges\ bank).$

Table V shows evidence on serial correlation and heteroscedasticity in conditional form for the OLS estimates reporting banks and Norges Bank, which is adjusted for by using the Newey West estimator. The other estimates: Customer order flow model, foreign banks, financial and non–financial customers show evidence of heteroscedasticity, which is adjusted by using the white correction matrix. Thus, the following t–values are the result of robust standard errors.

Table V. OLS regression of end – user flow

ΔReporting banks	ΔForeign banks	ΔFinancial customers	ΔNon-financial customers	ΔNorges Bank	**Adj. R^2**	**AC**	**Hetro**
-0.00289* *(-5.08)*					0.0343	0.0003 0.0045	0.000 0.000
	-0.00086* *(-16.65)*				0.342	0.1895 0.238	0.004 0.000
		0.00099* *(3.90)*			0.030	0.0001 0.0005	0.000 0.000
			0.00094* *(15.18)*		0.334	0.04 0.133	0.013 0.000
				-0.00043 *(-1.468)*	0.0054	0.000 0.001	0.000 0.000
-0.0000372 *(-0.074)*	-0.000466* *(-3.692)*	0.000177 *(0.894)*	0.000496* *(2.53)*	0.00000707 *(0.035)*	0.3635	0.156 0.139	0.0070 0.0000

Note: The table summarize result from OLS estimates of each end – user flow and the order flow end customer model on a weekly horizon for the period 03.10.2005 – 13.11.2016 with 579 observations. The explanatory variables is in Bn. Norwegian kroners. The explanation power is given in adjusted R square. The t – value is in parenthesis, and * indicate a significant level on 5%. The Greek letter Δ indicate first difference. The AC column show the p-value of a chi-squared test for residual autocorrelation, first-order in the top row and sixth - order in the bottom row. The Hetero column show the p-value of a chi-squared test for ARCH in the residuals, first-order in the top row and sixth-order in the bottom row. OLS estimates is adjusted for heteroscedasticity and serial correlation, using Newey West estimator and Huber White estimator.

The results in table V strongly indicates that the end–user impact on the exchange rate differs in terms of statistical significance and effect. The different segments are further investigated in detail in the next paragraphs.

Together reporting banks and foreign bank constitute the interbank market, where the former have a non – significant negative price effect, which is not intuitive according to standard theory. The adjusted R^2 is relatively low, which does not support the growing number of studies arguing that dealers bring their own private information (King et al. 2013). Foreign banks have the strongest explanatory power among segments and have a significant negative effect on the price, which implies that a net purchase pressure of euro (positive order flow) cause a decrease in NOK/EUR (the Norwegian kroners appreciate). This result is counter – intuitive and difficult to justify in an information related framework (Marsh and O'Rourke 2005). However, the liquidity effect might provide explanation, which is further explored in the next sub section.

Financial customers have a non-significant positive effect on the exchange rate, which is theoretically intuitive. Isolated, the segment's explanatory power at 3% is surprisingly low, considering that the vast majority of literature has found strong evidence that the financial end-user is the most informed customer segment (Fan and Lyons 2003; Evans and Lyons 2006, 2007; Menkhoff et al. 2012). An explanation for this conflicting result can be the relatively low trading volume percentage of 10% compared to studies like Fan and Lyons (2003) and Evans and Lyons (2006)[6]. This is considering that the portfolio shift has to be large enough to move the price (Evans and Lyons 2002).

The non – financial end – user flow has a significant positive effect on the exchange rate, which implies that a net purchasing pressure on euro results in a NOK/EUR increase, thus the Norwegian kroner depreciates. This is intuitive according to the standard theory, however empirical studies suggest that non – financial customers have a negative price effect (Evans and Lyons 2006; Bjønnes et al. 2005; Menkhoff et al. 2012). Isolated, the explanation power is 33 %, which is approximately the same as the foreign banks' adjusted R^2 (the highest among end–

[6] The financial order flow in terms of leveraged and unleveraged represent two third of the total volume.

user group). This was not anticipated, considering that non–financial customers' motive is assumed to secure revenue and cost, thus this segment's transaction flow should not reflect relevant information (Osler and Vandrovych 2009). However, empirical studies like Evans and Lyons (2007) and Rime et al. (2010) suggest that customer order flow can be used to predict upcoming macro statistics, thus the non - financial order flow can contain price relevant information. This might hold true considering that the petroleum sector's trades dominate the non – financial transaction flow, which is by far Norway's largest industrial sector (Norsk Petrolium 2016). Hence, this specific order flow can presumably reflect information about the state of the Norwegian economy, which is price relevant information.

At last, the customer segment Norges bank has a non–significant positive effect on the exchange rate with the lowest explanation power isolated against the price. Trades from this segment were anticipated to be non – informative, considering that Norges Bank has a non – profit based motive (Osler and Vandrovych 2009).

The results summarized suggest asymmetric information among market participants, where the non–financial customers' order flow is most informative, and not the anticipated financial customers' transaction flow. Hence, the order flow source is important. This results support Romstad's (2009) findings with the use of daily-disaggregated customer order flow from Norway's largest bank DNB.

4.3 Market roles

Heterogeneity among customer segments is examined in greater detail to identify market roles in the Norwegian currency market (NOK/EUR), where the result is interpreted according to the liquidity effect. The last row in table V shows that non-financial customers' order flow has a positive price effect and that foreign banks' transaction flow has a negative price effect, with equal coefficient in terms of absolute value. This indicates that the segments play opposite roles in the FX market. The non–financial customers positive price effect indicates that the segment's transaction flow convey private information and drives the exchange rate movements. On the contrary, the foreign banks negative price effect indicates that this customer segment are sensitive to price change and absorb the dealers' inventory imbalance, which implies that foreign banks provide liquidity in the market. This is supported by further analysis presented in table VI that shows that the segments are heavily negative correlated.

Table VI. End–user regression and VAR Granger causality test

ΔForeign banks = 1704.127 - 0.939449 * ΔNon – financial customers (-28.71)		R^2 = 0.7168
	Foreign banks	**Non – financial customers**
VAR Granger causality test	0.0055	0.3477

Note: ΔReporting banks are the foreign banks net foreign exchange purchase in millions NOK. ΔNon–financial customers is the net foreign exchange purchase in millions NOK. The OLS estimate is for the period 03/10/2005 - 07/11/2016 with 577 observations adjusted for heteroscedasticity and serial correlation using Newey West Estimator. Numbers in parenthesis represents robust t–values. Explanatory power is given in R–square. The second row present the dependent variable in the VAR estimates. The VAR Granger causality test row represent the chi square test given in p–value.

The bivariate VAR estimate for non – financial and foreign banks is applied to test for Granger casualty according to the T-Y method.[7] The purpose of the Granger causality test is to identify who is on the active (round one customers) and passive side (round three customers), if non-financial customers' order flow can forecast foreign banks' transaction flow, it implies that non-finanical customers are most likely not on the passive side (Bjønnes et al. 2005). The second row in table VI shows that we can reject the null hypothesis of no Granger causality from non-financial customers' transaction flow to foreign banks' order flow, where the opposite is not true. This supports the earlier evidence on distinctive market roles.

The findings can be interpreted in such way that the non–financial customers play the role of the typical round one active customers, which demand liquidity and that foreign banks act as the typical round three passive customers, which provide liquidity in the Norwegian currency

[7] The bivariate VAR–models includes weekly foreign bank and non – financial customers order flow specified after the T-Y method. This implies the use of non – stationary data series in level form, and adding an extra lag considering that the data sample is stationary in the first difference. The maximum lag is determined after the Akaike information criteria, which resulted in an optimal lag of four. The VAR LM test for serial independence is applied, and the model is absent from serial correlation.

market (NOK/EUR). This is in line with the evidence found in Bjønnes et al. (2005). However, the evidence deviates in terms of market roles, where the authors suggest that the financial customers are the aggressor and non–financial customers provides overnight liquidity.

4.4 Does customer order flow add value to a traditional model?

This section is investigating the in sample performance of the traditional macro model, where the price effect is assumed to be direct and immediate, in comparison to a hybrid model where both channels affect the price (Lyons 2001b). The result of this empirical analysis will give us an indication if order flow adds value to a traditional model. The traditional model[8] is estimated on the background of exchange rate models used by the central bank of Norway, where oil prices and interest differentials are essential (Naug 2003). The hybrid model[9] contains the fundamentals in the traditional model and the non–financial customer's order flow[10]. The variables in both the models are in first difference to overcome nonstationary, and adjusted for heteroscedasticity using the Huber – White estimator, since the residual diagnostic displayed in table VII show evidence of heteroscedasticity.

Table VII. Traditional model vs hybrid model

	ΔInterest differential	ΔlogOil Price	ΔNon–Financial customers	**Adj. R^2**	**SSR**	**AC**	**Hetero**
Traditional model	-0.028* (-3.36)	-0.086* (-7.97)		0.224	0.037	0.071 0.106	0.000 0.000
Hybrid model	-0.0205* (-2.75)	-0.053* (-5.00)	0.000764* (11.99)	0.415	0.028	0.237 0.605	0.547 0.000

Note: The table summarize OLS estimates of the traditional model and the hybrid model on a weekly horizon for the period 03.10.2005–13.11.2016 with 579 observations. The dependent variable Δlog NOK/EUR is the nominal exchange rate. The explanatory variable ΔInterest differential is NIBOR 3M – EURIBOR 3M, the Δlog Oil Price is the European crude oil price and the ΔNon – Financial customers is in Bn. Norwegian kroners. The explanation power is given in adjusted R square. SSR represent sum of squared residuals. The t–value is in parenthesis (adjusted for heteroscedasticity in the case of the traditional model) and * indicate a significant level on 5%. The Greek letter Δ indicate first difference. The AC column show the p-value of a chi-squared test for residual autocorrelation, first-order in the top row and sixth -order in the bottom row. The Hetero column show the p-value of a chi-squared test for ARCH in the residuals, first-order in the top row and sixth-order in the bottom row.

[8] The traditional model: *Δlog(NOK/EUR) = β0 + β1Δ(Interest differential) + β2Δ log(Oil price)*

[9] The hybrid model: *Δlog(NOK/EUR) = β0 + β1Δ(Interest differential) + β2Δ log(Oil price) + β3 Δ (Non – Financial Customers)*

[10] Non – financial order flow is chosen as the order flow explanatory variable, considering that previous result indicated that this segment was most informed.

The results from table VII show that the hybrid model performs significantly better than the traditional model with a higher adjusted R^2 and a lower sum of squared residuals (SSR). This indicates that order flow is complimentary to the fundamental variables. In addition , the non–financial transaction flow is the most significant variable in the hybrid model and contributes with a 19.1% higher adjusted R^2 , which suggest that customer order flow plays a prominent role when modeling the exchange rate for a short horizon . The results are in line with earlier empirical studies like Evans and Lyons (2002, 2006) and Romstad (2009), where order flow based models perform better in sample than traditional models.

4.5 Out of sample

This section investigates customer order flow's ability to predict price movements, by using modified in sample model estimates presented earlier in this dissertation[11]. The out of sample analysis includes one-step ahead and dynamic predictions based on 566 observations with the remaining 12 observations (12 weeks) withheld for testing. The one-step ahead forecasts are based on recursive estimates of models where the change in exchange rate today depends on variation of lagged values of order flow and macro fundamental variables. This implies that the models are re-estimated for each prediction period using actual realized values from the previous period. The dynamic forecasts are based on VAR – models, where the change in exchange rate today depends on variation of historically values of NOK/EUR return, change in end–user flow and macro fundamentals. This implies that the models use predicted values of the previous term, instead of realized values to forecast the next period. The naïve random walk model without drift[12]is used as a benchmark to assess the models performance with the evaluation criteria root mean square error (RSME) and the change of directions (COD) [13]

[11] The traditional model and the hybrid model I was presented in section 4.4 and the hybrid model II consist of lagged values of Δ Interest differential, Δ log Oil Price and Δ Foreign banks Order flow.

[12] A model where the previous period value of the exchange rate is used to predict the current exchange rate.

[13] The change of direction criteria evaluate the models ability to predict the exchange rates direction (the sign of the predicted value and the actual value are compared, where an equal sign counts as 1/12).

Table VIII. One - step ahead forecast

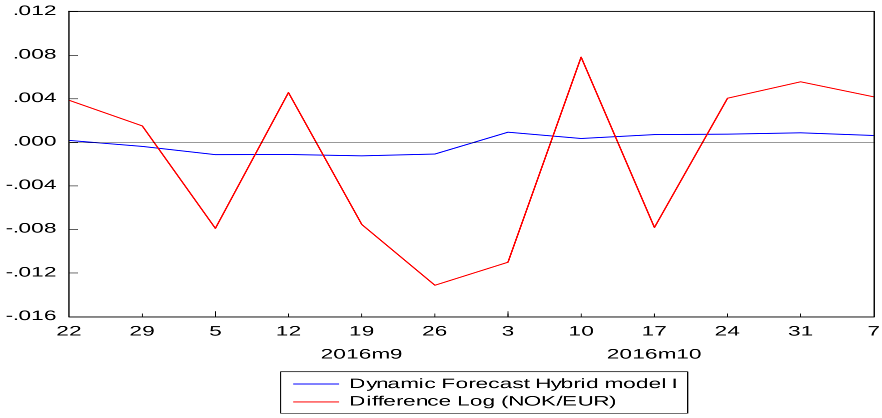
	RSME(*100)	COD
Random walk	0.7370	5/12
Traditional model	0.7671	5/12
Hybrid model I	0.7211	4/12
Hybrid model II	0.6599	6/12
Foreign banks	0.6017	8/12

Note: The weekly forecasts are based on recursive estimates starting with 566 observation, with the remaining 12 observations withheld for out of sample testing. The RSME column represents the root mean square error. The COD column presents the models ability to predict direction, where the same sign counts as 1/12.

Table VIII presents the results for the static forecast for several models on a weekly horizon. The results indicate that the micro–based models slightly outperform the fundamental and random walk model in terms of RSME, which is in line with Rime et al. (2010), Menkhoff et al. (2012) and Evans and Lyons (2002, 2005). The latter show evidence that micro-based models consistently out-performs the random walk and macro fundamental models on a horizon spanning from one to 20 trading days. The right column in table VIII displays the models ability to forecast the direction of NOK/EUR return. The results indicate that the order flow based models, except for the hybrid model I, are better at predicting the return direction than the random walk and the traditional model. The order flows ability to predict the exchange rate direction can be highly valuable for agents in the FX market trading with the purpose of payoffs.

The dynamic forecasts based on VAR models estimates flat out immediately after the first period making the result uninformative, which is illustrated in Figure II for the hybrid model I. The result has the same outcome for all the VAR models estimated, which can be due to the lack of multiple existing relationship between the variables, considering that the VAR models use each other's previous predicted values to forecast the next period.

Figure II. Hybrid model I dynamic forecast



In summary, the findings appear promising with the micro–based models ability to out–perform the random walk model and the traditional model for the statistical forecasts. However, it is too early to conclude considering that the dynamic forecasts are uninformative.

5. Conclusion

The customer order flows' role in the Norwegian currency market has been examined in this thesis, which gave insights on order flows ability to explain the exchange rate in sample and out of sample on a weekly horizon. Historically the performance of macro fundamental models have been poor in sample and out of sample for high frequency horizons. These disappointing results gave room for a new theoretical direction to emerge. Instead of assuming that the exchange rate does only depend on macro fundamentals, the microstructure theory includes the order flow determinant as a vehicle that compound information into price in the FX market.

Disaggregated order flow data from Norges Bank is used to analyze the relationship between end–user flow and the exchange rate (NOK/EUR). The results from the co-integration test indicated that none of the customer segments trades had an existing long-term relation to the exchange rate. This implies that the customer order flow has a non–permanent effect on the price. However, a series of empirical studies finds supporting evidence for the opposite (Rime and Sojli 2006).

The results from the customer order flow regressions indicated that foreign banks had the highest explanatory power, however this segment had a negative effect, which is counter-intuitive according to standard theory. Reporting banks had a non – significant negative price effect, which is not intuitive. The segment's adjusted R^2 was relatively low, which does not support empirical studies indicating that dealers carry relevant information into the FX market (King et al. 2013). Non – financial customers had marginally the second highest explanatory power on the exchange rate movements, with a positive price effect, which is intuitive. An explanation for the unanticipated high correlation could be that non – financial customers' flow reflects information about the state of the economy, thus is informative (Evans and Lyons 2007; Rime et al. 2010). The financial customers were anticipated to be the most informed customers, however the result shows that this segment was non–significant and had a negligible explanatory power. This could be due to the relatively low transaction volume, considering that the portfolio shift has to be of a certain size to move the price. As expected Norges Bank had a non–significant positive price effect and a low explanatory power. The customer segments' order flows differed in terms of significance and effect, suggesting asymmetric information among market participants, which supports Romstad's (2009) findings. Thus, the order flow source is important.

The robust evidence for a liquidity effect in the NOK/EUR market is intriguing. The results show that net purchase of foreign banks and non–financial customers have approximately the same absolute coefficient with significant opposite effect on the exchange rate. Further supporting evidence indicates that the segments are heavily correlated and that non–financial customers' transaction flow Granger cause foreign banks' order flow, where the opposite is not true. This indicates that non–financial customers demand liquidity, which is provided by foreign banks. These findings are consistent with Bjønnes et al. (2005), except that the authors find that financial customers are the aggressor and that non–financial customers are the ultimate liquidity provider.

The hybrid model performs better than a traditional model in sample, suggesting that order flow add value to a traditional model and is complimentary to fundamentals. This evidence supports the findings in Evans and Lyons (2002) and Romstad (2009). In the statistics forecasts, the micro-based models out–performed the traditional model and a naïve random walk in terms of RSME, which supports the finding in Evans and Lyons (2002, 2005), Rime et al. (2010) and Romstad (2009). However, the dynamic forecasts is uninterpretable with predictions that flat out immediately after the first prediction period.

In conclusion, the key findings suggest heterogeneity among agents, where non-financial customers and foreign banks play opposite roles in the Norwegian currency market. Non–financial customers' order flow is the primary information source that drives price movements and foreign banks' transaction flow provide liquidity in the market. However, the segments' effect on price is non-permanent. Customer order flow is complimentary to the traditional fundamentals and play a prominent role when modeling the exchange rate on a short horizon. In a forecast setting, order flow based models' result for the one-step ahead forecast is promising, however the dynamic predictions are inconclusive and further analysis is necessary.

In terms of limitations multicollinearity occur in the customer order flow model in section 4.2, considering that the explanatory variables foreign banks and non-financial customers' flow are heavily correlated. The consequence is overinflated standard errors, which might lead to significant variables becoming insignificant. Another limitation is that the models are only tested for a weekly horizon and one currency pair.

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