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A hybrid approach to exchange rate dynamics: How do macro variables and order flow affect the Norwegian Krone?

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by
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MSc in Business with Major in Finance

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ABSTRACT

This paper investigates the relationship between the EURNOK spot exchange rate, macroeconomic factors, and order flow. We consider an error correction model framework using almost 16 years of data. At a weekly frequency, we establish a link between the EURNOK depreciation rate and changes in the 3–month interest rate differential between Norway and the Euro area, the Brent Crude Oil price, and volatility in the financial market. Our findings confirm that different end–user order flows are empirically important drivers of movements in the exchange rate and convey additional information. The results are stable across subsamples, and in an out–of–sample fit exercise, we present evidence that the hybrid model outperforms the random walk benchmark.

Acknowledgements

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1 Introduction

The Norwegian economy is influenced by several factors, among them the Krone exchange rate. Thus, a compelling question is what factors affect the exchange rate and to what extent. In this thesis, we study the movements in the Norwegian Krone against the Euro (EURNOK)[1] in relation to traditional macroeconomic factors and the microstructure theory. Specifically, we examine its relationship with the 3–month interest rate differential between Norway and the Euro area, the Brent Crude Oil price, and an implied volatility index, in addition to aggregate Financial and Non–financial end–user order flows at a weekly frequency. We specify the research question as:

How do macroeconomic factors and end–user order flows influence the Norwegian exchange rate at a weekly frequency?

We use almost 16 years of high–quality data on disaggregated order flows from the Norwegian Krone (NOK) market obtained from Norges Bank. Evans and Rime (2016) apply a similar data set ranging from October 2005 to the end of 2013, whereas our sample ends in February 2021. A unique feature of our data is its length which enables a more extensive stability assessment of our findings. Additionally, we utilize the fact that our sample covers periods of heightened volatility in the variables. Primarily, existing research examines the relationship between exchange rate movements and order flow using other currencies. Our focus is on the Norwegian exchange rate and how this research adds to previous studies (e.g., Bjønnes et al., 2005; Chinn & Moore, 2011; Evans & Lyons, 2002).

[1] We define the EURNOK exchange rate as the price of EUR expressed in terms of NOK (NOK/EUR).

Our motivation in conducting this study is the behavior of the Krone exchange rate over the past decade. The development is characterized by significant fluctuations with respect to the Euro and the U.S. dollar and an apparent weakening of the NOK after 2013 (NOU 2020: 8, p. 139). Following the Financial Crisis, Norway experienced economic growth and stability and relished the benefits of the oil boom and a stronger Krone exchange rate. However, a plunge in oil prices after 2014 followed by the trade war between China and the U.S. and the 2020 price war between Saudi Arabia and Russia contributed to a sustained lower oil price level.

Norway is a large oil and gas exporter, and the conventional perception is that there exists a relationship between the Norwegian Krone and oil prices. Norway is frequently mentioned in the context of commodity currencies and the predictive ability of oil prices (e.g., Akram, 2004, 2020; Bernhardsen & Røisland, 2000; Ferraro et al., 2015). Economic theory links sustained high oil prices to favorable terms of trade for oil–exporting countries, which in isolation should result in a strengthening of the exchange rate (Bernhardsen & Røisland, 2000). Observations of monetary measures and oil price tendencies not necessarily coinciding with the direction of the Krone entails a comprehensive discussion of potential factors that might contribute to explaining the dynamics of the Krone exchange rate. Bernhardsen and Røisland (2000) show that the Krone is affected by turbulence in the financial markets, and according to Akram (2020) smaller, less liquid currencies, like NOK, are vulnerable to financial and geopolitical global risk due to capital flights. Periods of uncertainty are unfavorable for the NOK as it is not regarded as a safe haven.

There is extensive research on macroeconomic models of exchange rates. However, following Meese and Rogoff's (1983, 1988) work, there is limited evidence of macroeconomic fundamentals that are reliable for exchange rate explanation and forecasting. The emergence of a new exchange rate literature, microstructure theory, highlights variables the conventional macro models omit. A common micro variable is order flow which is defined as the difference between the value of buyer–initiated and seller–initiated orders for foreign currency (Evans, 2009). According to Lyons (2001), order flow convey relevant information about fundamentals and accounts for a considerable part of the fluctuation in spot rates in the FX market.

In accordance with Evans and Rime (2016) we aggregate the order flows into two different end–users: Financial and Non–financial customers. This allows us to address the various roles the market participants play and how they are related to variations in the exchange rate. Building on existing literature (e.g., Evans and Rime, 2016; Bjønnes et al., 2005) we examine exchange rate models augmented with the two order flow variables to account for private information and beliefs about the exchange rate. The model is a hybrid of the traditional exchange rate model with macroeconomic fundamentals and the microstructure approach seen in Evans and Lyons (2002).

Our results indicate that a hybrid model including public and private information explains a considerable part of the fluctuations in the EURNOK exchange rate. A positive and significant relationship is established between changes in the exchange rate and the Financial customers and a negative relationship between changes in the exchange rate and the Non–financial customers. We find that the exchange rate is cointegrated both with cumulative Financial order flow alone and including macroeconomic fundamentals, which suggests that the effects are permanent. However, the results do not provide evidence in support of a cointegrating relationship between the exchange rate and Non–financial order flow. These results also persist when considering subsamples. Overall, a subsample analysis reveals that the results are pretty stable over time, regardless of the Financial Crisis. We also find that the hybrid model outperforms the random walk benchmark and a simple micro model in terms of predictive ability in an out–of–sample fit exercise.

The remainder of this thesis is organized as follows: the next section is a literature review of the theory and previous findings within the field. Section 3 describes the model and methodology we use to identify how the variables drive changes in the exchange rate. The specification of the data and descriptive statistics are described in section 4. Section 5 presents our results and analysis, including interpretations and discussions of our findings, while section 6 concludes.

2 Literature Review

2.1 Macroeconomic Models

There is an abundance of research investigating the relationship between exchange rate fluctuations and macroeconomic fundamentals. Macro models of floating exchange rates build on fundamentals such as prices, money– and output differentials, interest rates, and inflation. Two established theories are Purchasing Power Parity (PPP) and The Uncovered Interest Rate Parity (UIP).

PPP claims that the real price of a basket of goods in one country should equal the real price of a basket of comparable goods in another country, implying that the currencies should have the same purchasing power (Rossi, 2013). According to Rogoff (1996), the literature provides a consensus regarding evidence of the real exchange rate tending toward PPP in the very long run; however, the speed of convergence is slow. Further, the deviations from PPP in the short run are quite large and volatile. Akram (2000a) tests the PPP between Norway and its trading partners and finds evidence in the long run, converging toward equilibrium.

UIP relates the difference between interest rates expressed in two countries to the expected change of the exchange rate (Dimand, 1999). The theory states that a high–interest rate country should exhibit a depreciation with respect to a country with a lower interest rate. Meese and Rogoff (1988) explores the relation between the real exchange rates and the real interest rate differentials. They find limited evidence in favor of the UIP as their results do not offer an improved forecasting ability of real exchange rates over the random walk. Meese and Rogoff (1983) compare the out–of–sample forecasting accuracy of several exchange rate models and find that the random walk performs just as well as the structural models even though the forecasts are based on realized fundamentals. Obstfeld and Rogoff (2001) introduces the phrase "the exchange rate disconnect puzzle", acknowledging the weak short–run relationship between macroeconomic variables and the exchange rate.

Cheung et al. (2005) also uses the random walk as a benchmark. Their results support the findings of Meese and Rogoff (1983) in terms of the lack of outperformance of fundamentals with respect to the random walk, presenting further evidence on the exchange rate puzzle. Even though the UIP for some countries forecasts better than the random walk over longer horizons, it is not significantly superior. They also find that the out–of–sample evidence for PPP is deficient. Although PPP, for sufficiently long horizons, predicts better than the random walk, the results are not significantly better. At shorter horizons, it performs significantly worse.

Economic theory predicts that oil–exporting countries will experience a strengthening of their exchange rate given a sustained rise in oil prices (Bernhardsen & Røisland, 2000). Chen and Rogoff (2003) focus on OECD economies when investigating the determinants of real exchange rate movements and find a solid and stable relationship for some of the countries. They look at well–developed small open economies with primary commodities constituting significant shares of their exports, making them eligible as "commodity economies". The commodity prices can be regarded as exogenous to the countries, thus potentially explaining a significant part of their terms–of–trade fluctuations. Ferraro et al. (2015) show the existence of a short–term relationship at a daily frequency between commodity prices of commodity–exporting countries and their nominal exchange rates. Their results suggest that commodity prices predict the currency's exchange rate at a daily frequency; however, the predictive ability is not evident at a monthly or quarterly frequency. Akram (2000b) investigates a linear relation between oil prices and the Norwegian exchange rate and whether such a relation underestimates the effect of significant changes to oil prices on the exchange rate. He unveils that the relationship varies with the levels and trends of the oil prices and finds upper and lower bounds for "normal" oil prices. He investigates a non–linear relation between commodity prices and exchange rates and finds that the non–linear models outperform the linear models; however, this is only significant in the short run.

Bernhardsen and Røisland (2000) also investigate how the Krone exchange rate is influenced by turbulence in international financial markets. They use the Global Hazard Indicator (GHI) as an indicator of international financial turbulence and find that, from a short–term perspective, financial turbulence has been an essential driver of fluctuations in the Krone exchange rate since 1997. An increase in the GHI leads to a temporary weakening of the NOK, most likely because international agents are inclined to reduce their Norwegian Krone holdings in periods of high volatility in international financial markets. Further, Kohlscheen et al. (2016) show that variations in global risk and risk appetite, as proxied by the Chicago Board Options Exchange Volatility Index (CBOE VIX), has an influence on currency movements and that the VIX does not drive the predictive accuracy of commodity prices. According to Akram (2020), a large number of currencies, among them the Norwegian Krone, have been sensitive to financial market risk after the Financial Crisis. Consequently, capital flights of small currencies, like NOK, tend to increase with the volatility measure VIX.

2.2 New Perspectives – Microstructure

Since the publication of Meese and Rogoff (1983) there is limited evidence of macroeconomic variables that are reliable predictors for exchange rate behavior. However, since the 1990's a new literature has emerged; the microstructure approach. The FX market has a huge trading volume which is not accounted for when mapping macroeconomic variables to the behavior of exchange rates. The microstructure approach links exchange rates to the flows of transactions between counterparties in the foreign exchange rate market. Previous studies neglect the interaction between the two and approach them independently of one another (Lyons, 2001). Evans and Lyons (2002) and Lyons (2001) address this growing approach to exchange rates. This theory does not assume homogeneous expectations of the market participants, implying that the market alone holds information that might impact the exchange rate. Lyons (2001) points out how the microstructure approach relaxes three of the assumptions of the asset–based approach. The approach recognizes that; some information relevant to exchange rates is not publicly available, market participants differ in ways that affect prices, and trading mechanisms differ in ways that affect prices.

Two new variables emerge when moving from a macro to a micro approach: order flows and spreads. We focus on order flows in our thesis. Order flow is the signed transaction volume and has a negative sign if the initiator sells and a positive sign if it buys. If the sum is negative, it implies a net selling pressure (Lyons, 2001). Lyons attempts to establish a link between macro and micro approaches by mapping public and nonpublic information to price. Evans and Rime (2016) examine order flows as drivers of spot exchange rate dynamics and find that it has significant incremental forecasting power over longer horizons than previously shown in the literature. They also unveil distinct periods during the Financial Crisis and the European debt crisis where the order flow information regarding risk premia affected the EURNOK rate. Chinn and Moore (2011) combine the monetary model and Evans–Lyons's microstructure model and show that the combined model surpasses both the monetary model and a random walk in a forecasting exercise. Their focus is on the argument that order flow provides public dispersed private information about risk premia, meaning that the order flow reveals information that is never made public.

Evans and Lyons (2002) introduces a stylized trading model where each day is divided into three trading rounds. In round one, dealers trade with the public using information available to all participants. The dealers share the inventory risk in round two by trading with each other. Finally, in round three, the dealers trade with the public to encourage them to absorb inventory imbalances. Bjønnes et al. (2005) examine the liquidity provision in the overnight foreign exchange market in Sweden, where they specifically distinguish between Non–financial and Financial customers in the FX market. Considering that the dealers' inventory is absorbed in round three, the first and third round customer orders should have opposite signs and of similar size. They find that, in the long run, Non–financial customers are the liquidity providers in the overnight foreign exchange market for the EURSEK exchange rate and that Financial customers usually “push” the market. There are two main findings they highlight when explaining these results. First, the net position of Non–financial customers is negatively correlated with the exchange rate, as opposed to the opposite being true for Financial customers. Second, the changes in the net position of the Non–financial customers are forecasted by changes in net position of Financial customers. In other words, Non–financial customers take a passive role consistent with liquidity provision.

3 Methodology

This section presents the methodology we use to investigate the relationships between the exchange rate and the variables in question. First, we examine the links between order flows, macroeconomic variables and the exchange rate. Second, we apply a cointegration and error correction methodology to explore both the short– and long–term effects. Finally, we assess the stability of our findings and the forecast ability compared to a random walk. Our empirical analysis is in the spirit of Evans and Rime (2016) and Bjønnes et al. (2005), where the order flows of Financial and Non–financial end–users are treated separately. Additionally, we include the Brent Crude Oil price, the 3–month interest rate differential between Norway and the Euro area, and the CBOE Volatility Index (VIX) as a parameter of uncertainty.

Lyons (2001) and Evans and Lyons (1999) describes the informational features of trades as the primary distinction between the asset approach and microstructure approach. Under the asset approach, macroeconomic information is public and drives the price directly, and trades play no role. Microstructure models focus on fundamental information, which is not publicly known, and information is translated into order flows, making trades the primary driver.

Combining elements from both approaches make it possible to establish a link between the micro– and macro determinants. Equation (1) is a representation of the hybrid model discussed in Lyons (2001) and Evans and Lyons (1999).

$$\Delta s_t = f(\Delta i, \Delta m, \dots) + g(\Delta x, \Delta I, \dots) + u_t \tag{1}$$

Δs_t is the log change in the nominal exchange rate, the function $f(\Delta i, \Delta m, \dots)$ is the macro element containing, for instance, the change in interest rates, money supply and other macroeconomic determinants, while the function $g(\Delta x, \Delta I, \dots)$ can include order flow, inventory, and other microeconomic determinants (Evans and Lyons, 1999).

We analyze the data using a hybrid model inspired by Lyons (2001). To evaluate the time–series properties, we use the augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The null hypothesis under the ADF test is non–stationarity, while the null hypothesis under the KPSS test is stationarity (see Appendix A.1 for details). We estimate price impact regressions for various specifications to examine the contemporaneous relationship between the variables and the log change in the exchange rate.

To assess whether there is a long–run relationship between the exchange rate and cumulated order flows we first test if the log level of the EURNOK exchange rate is pairwise cointegrated with Financial and Non–financial order flows. Next, we extend the cointegrating equation to include the macro variables. Two tests are implemented: the Johansen trace test and the Engle–Granger (1987) cointegration test (see Appendix A.2 for details). The Johansen (1988) test is performed by constructing two Vector Error Correction models (VECM). Each contains the separate cumulative order flows, the EURNOK exchange rate, and the macro variables when the cointegrating analysis is extended to a hybrid model. The Engle–Granger test is carried out on a single cointegrating regression with log EURNOK exchange rate as the dependent variable.

Error Correction model

If a cointegrating relationship is established, an Error Correction Model (ECM) is estimated to preserve the long–run solution focusing on the exchange rate equation. A combination of first differenced and lagged levels of the cointegrated variables results in a model for short–run dynamics and the rate of adjustment to the long–run equilibrium. Equation (2) and (3) demonstrate the two ECMs of interest.

$$\Delta s_t = \alpha + \beta \Delta x_t + \phi(s_{t-1} - \gamma x_{t-1}) + u_t \tag{2}$$

$$\Delta s_t = \alpha + \Delta X_t B + \phi(s_{t-1} - X_{t-1}\Gamma) + u_t \tag{3}$$

Here s is the log EURNOK exchange rate, x is cumulative order flow and X is a vector of macro fundamentals and cumulative order flow. $s_{t-1} - \gamma x_{t-1}$ and $s_{t-1} - X_{t-1}\Gamma$ are the error correction terms obtained from the cointegrating regressions with s as the dependent variable. γ is the cointegrating coefficient that defines the long run relationship between x and s, while Γ is the vector of cointegrating coefficients. The short–run relation between the changes in x (X) and s is represented by β (B), while ϕ shows the speed of adjustment back to the equilibrium.

To examine the robustness of the results, we divide the sample into two subsamples. The first sample corresponds to Evans and Rime's (2016) sample from October 2005 to December 2013, excluding the Financial Crisis. The second sample is the remaining half of our data set, from January 2014 to February 2021. The stability of the results are also assessed based on an inclusion and exclusion of the Financial Crisis and the COVID–19 pandemic. Additionally, we implement the Diebold and Mariano (1995) and Clark and West (2006) test of forecast accuracy to evaluate the forecasting performance of the model compared to random walk benchmarks (see Appendix A.3 and A.4 descriptions of the tests).

4 Data and Descriptive Statistics

The analysis focuses on the EURNOK exchange rate at a weekly frequency. We use end–of–sample data on three macroeconomic series to account for the public information available to the market participants. The macroeconomic series includes the Brent Crude Oil price, the CBOE Volatility Index (VIX), and the interest rate differential between the 3–month interest rates in Norway and the Euro area. The fundamentals we use somewhat coincides with previous literature. For instance, Akram (2020), Bernhardsen and Røisland (2000), and Kohlscheen et al. (2016) use oil prices, interest rate differentials and an indicator of financial turbulence in their analysis. We collect weekly data from the Bloomberg Terminal based on the last trading price and take the natural logarithm of all variables except the interest rates.

The order flow data is retrieved from Norges Bank. They provide us with weekly end–user transactions based on daily turnover data from the foreign exchange market. Our sample period is limited by the availability of order flow data which spans from October 2005 to February 2021, containing 803 weekly observations. Note that analogous to Evans and Rime (2016) the initial analysis is conducted excluding the Financial Crisis (July 2008 to June 2009).

4.1 Macro Factors

Exchange rate

The most traded currency pairs in Norway are EURNOK and USDNOK. As of April 2019, the daily spot trading volume of EURNOK was USD 17.5 billion while trading in USDNOK was USD 18.7 billion (Bank for International Settlements, 2019). Since the Euro serves as the main vehicle currency in Europe, the interdealer spot trading volumes traded in EURNOK are huge (King et al., 2011). Accordingly, we focus on nominal exchange rates for NOK/EUR in our thesis.

Today, Norway has a market–based exchange rate. Between 1992 and 2001, the Norwegian monetary policy changed radically as the currency went from being a pegged currency to a currency with a floating exchange rate system. The new system had a target to achieve low and stable inflation, and although it was floating, it was relatively stable until 1997. After 1997, the Norwegian currency experienced years of instability, and the discussion of the NOK and inflation management began to unfold. Finally, in 2001 new guidelines for economic policy, including rules of action, inflation targets, and the fiscal spending rule, were approved by the government (Kleivset, 2012; Saskia, 2016).

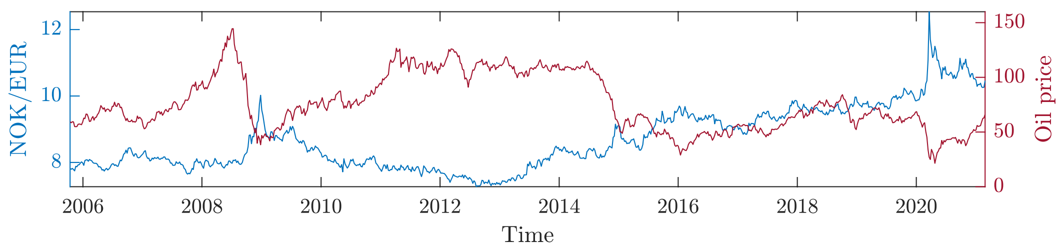
The EURNOK exchange rate traded relatively stable between 2005 and 2013, excluding the abnormal levels during the Financial Crisis. However, by mid–2013, the exchange rate steadily increased, reaching an all–time high in March 2020. This development shows that the Norwegian exchange rate has kept depreciating against the Euro.

Oil price

Norway is a substantial supplier of crude oil, and as of 2020, oil and gas represented 42% of Norway's export of goods (Norsk Petroleum, 2020). Hence, crude oil represents a considerable part of Norwegian export and the overall economy, and consequently, it could be an essential driver of the movements of the Krone exchange rate. Economic theory suggests that an increase in commodity prices affects the terms of trade for a commodity–exporting country and thus influences exchange rates. In isolation, this will result in an appreciation of their currency due to increased supply of foreign exchange in the market (Bernhardsen & Røisland, 2000; Kohlscheen et al., 2016).

West Texas Intermediate (WTI) and Brent Crude Oil (Brent) are the main benchmarks for crude oil. Most studies use the WTI index to collect data from the prices of WTI Oil. We use Brent Crude Oil as it is extracted from the North Sea as a blend of several crude oils (Leonard et al., 2020). Like Akram (2020) we collect data for Brent Crude Oil in USD per barrel. These are futures contracts, but we use them as a proxy for spot oil prices. Figure 1 plots the evolution of the Brent Oil price against the nominal EURNOK exchange rate. Note that an increase in the exchange rate seems to coincide with a depreciation of the NOK.

Figure 1: Oil price and EURNOK exchange rate

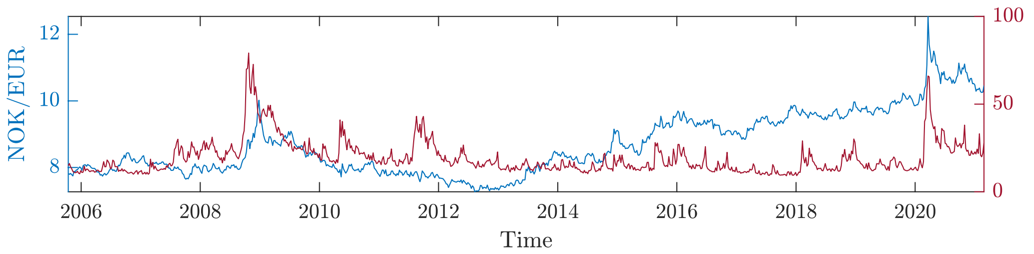


Notes. The figure shows the NOK/EUR exchange rate (blue, left–hand axis) plotted against the Brent Crude Oil price denominated in U.S. dollars (red, right–hand axis) from 14.05.2005 to 26.02.2021.

CBOE Volatility Index

Kohlscheen et al. (2016) finds that changes in risk and uncertainty convey information that explains exchange rate movements and is unrelated to changes in commodity prices. According to Bernhardsen and Røisland (2000), the currencies of small countries appear to depreciate in times of turbulence in the financial markets. The Norwegian Krone is regarded as a "peripheral" currency. Thus, international traders are likely to reduce their holdings in NOK during volatile periods, which in turn leads to depreciation. We retrieve the Chicago Board Options Exchange Volatility Index (VIX) to proxy for international financial uncertainty. It measures the 30–day volatility of equity markets using the implied volatilities of a wide range of S&P 500 index options. It serves as a proxy for risk–on–risk–off episodes in the global financial markets resulting in global investors moving in and out of foreign exposures. In Figure 2 we see the development of the CBOE VIX compared to the EURNOK exchange rate. The plot indicates that an increase in international financial uncertainty leads to a weaker Krone exchange rate.

Figure 2: CBOE Volatility Index and EURNOK exchange rate

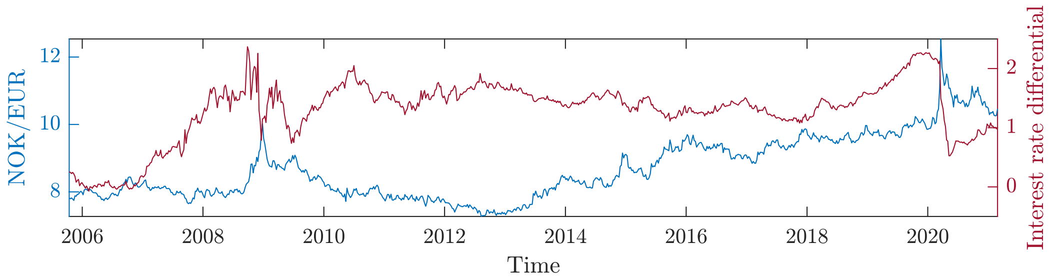


Notes. The figure shows the NOK/EUR exchange rate (blue, left–hand axis) plotted against the CBOE Volatility Index (red, right–hand axis) from 14.05.2005 to 26.02.2021.

Interest rate differential

It is common to measure interest rate differentials with money market interest rates. Like Rime and Solji (2006), we use the Norwegian and Euro area 3–month interest rates to construct the interest rate differential between Norway and the Euro area. Interbank interest rates serve as benchmark rates for several instruments and are designed to indicate the cost of unsecured lending between banks (Bernhardsen et al., 2012). It is determined based on the market's anticipations regarding the policy rate over a certain period, including a risk premium. The differential is calculated by subtracting the 3–month Euro Interbank Offered Rate (EURIBOR) from the 3–month Norwegian Interbank Offered Rate (NIBOR). Figure 3 shows that, on average, the interest rate differential is positive and relatively stable, with the exception of a few outliers during the Financial Crisis and the COVID–19 pandemic. Further, there seems to be a negative relationship between the EURNOK exchange rate and the interest rate differential. Descriptive statistics of the macro variables are reported in Table 1.

Figure 3: Interest rate differential and EURNOK exchange rate



Notes. The figure shows the NOK/EUR exchange rate (blue, left–hand axis) plotted against the interest rate differential between the 3–month in Norway and the Euro area (red, right–hand axis) in percentage from 14.05.2005 to 26.02.2021.

Table 1: Descriptive statistics: spot and macro–variables

	Mean	Median	St. Dev.	Skew.
Δs_t	0.022	-0.056	1.147	1.879
Δp_t	0.109	0.386	4.657	-0.382
Δi_t^{diff}	0.002	0.001	0.060	-1.795
Δvix_t	0.071	-1.026	15.442	0.742

Notes. The table reports descriptive statistics for 751 weekly observations of the macro–variables from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). Δs_t, Δp_t, and Δvix_t represent the one–week difference of the natural logarithm of the EURNOK exchange rate, the Brent Crude Oil price denominated in US dollars and the CBOE Volatility index. Δi_t^{diff} is the one–week difference of the interest rate differential between Norway and the EU. All values are measured in percent.

4.2 Micro Factors

Order flow

Analyses involving order flow have provided valuable insights regarding exchange rate movements. Exchange rates can both be influenced through direct and indirect channels (Evans & Lyons, 2005). The direct channels consist of publicly available information, which can be explained by the macro factors described above. It is assumed that all market makers receive the same information and have identical expectations of future economic development (Meyer & Skjelvik, 2006). The indirect channel functions through private information. This information is often described as micro–level knowledge, which can be the knowledge of earnings, buy and sell orders, and financial analyses, leading to different expectations regarding exchange rate developments. Although it may take time to interpret and implement the signals, order flow theory can indicate the direction of any exchange rate adjustments (Meyer & Skjelvik, 2006).

We collect information about the foreign exchange transactions from Norges Bank. The dataset consists of reporting banks' purchase and sale of NOK for foreign exchange, the different counterparties involved in the transaction, and contract type. The dataset ranges from the beginning of October 2005 to the end of February 2021. Evans and Rime (2016) apply a similar dataset. However, their data differs somewhat from what is publicly accessible for us. They have data on daily disaggregated currency transactions solely in the EURNOK market, while our data is on weekly currency transactions where the Norwegian Krone enters the currency pair. Further, their dataset contains the purchase and sales of nine different groups. Our dataset divides the counterparties of the trades into these five categories; Reporting banks, Foreign banks, Financial clients, Non–financial clients, and Norges Bank.

Although our dataset has differences, we construct order flows from the similarly defined groups of end–users to create Financial end–user order flow and Non–financial end–user order flow. The Financial end–users consist of foreign banks, financial clients, and Norges Bank, while the Non–financial end–users only include Non–financial clients. Motivated by the Evans and Lyons' (2002) three round model discussed in the Literature review, we focus on the first and third round, where the first–round customers are the active traders and the third–round customers are passive and provide liquidity. Like Bjønnes et al. (2005), we interpret the aggressive customer as being Financial and the passive liquidity provider as being Non–financial.

Positive numbers in the data sample indicate a net purchase of foreign exchange (EUR), which in our case implies that the reporting banks sell NOK. In line with Evans and Rime, we carry out the analysis with the counterparty's perspective, and thus we change the signs of the order flows. Additionally, we denote the transactions in EUR. Descriptive statistics of the aggregate Financial and Non–financial order flows and their subgroups are reported in Table 2. Like Evans and Rime (2016) we find that the Financial flow is more volatile than the Non–financial flow, especially the flows coming from Foreign banks.

Table 2: Descriptive statistics: end–user order flow

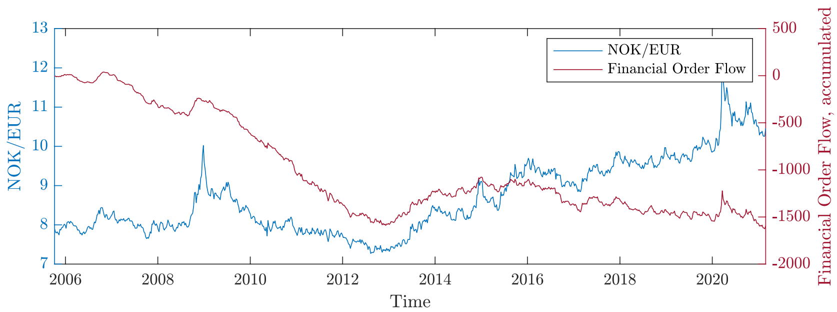
	Mean	Median	St. Dev.	Skew.
Financial flow	-2.591	-2.368	7.890	-0.229
Foreign banks	-1.176	-1.173	7.283	0.062
Norges bank	-0.225	0.000	2.261	0.242
Financial clients	-1.191	-0.220	3.668	-1.728
Non–financial flow	0.282	0.449	4.237	-0.218

Notes. The table reports descriptive statistics for weekly observations on aggregate financial and non–financial end–user order flows and the subgroups from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). It contains 751 weekly observations. The order flows are measured in EUR 100 million. Financial order flow includes the trades of foreign banks, the Norges Bank, and financial clients.

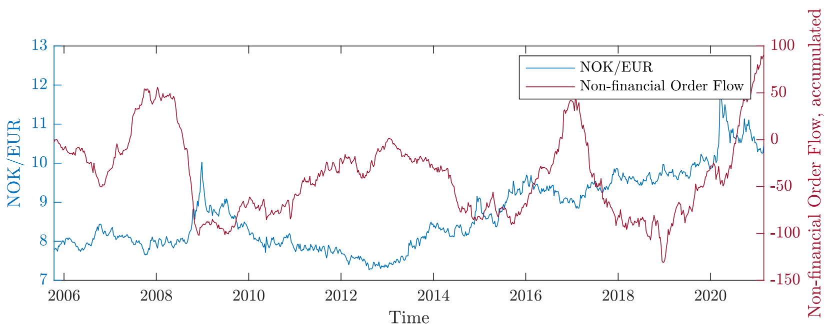
The Norges Bank data distinguishes between spot, forward, and swap transactions, and in line with Evans and Rime, we focus on spot transactions. This is because spot transactions are the dominant instrument traded in the foreign exchange market, and a swap is by definition a position that nets itself out (Bjønnes et al., 2005). Figure 4 shows the development of the accumulated Financial– and Non–financial end–user order flow compared to the EURNOK exchange rate. We observe that Financial order flow seems to be positively correlated with the Krone exchange rate from the plot. In contrast, Non–financial order flow is negatively correlated with the exchange rate. This corroborates the findings of Lyons (2001) and Bjønnes et al. (2005) that end–user order flows convey different information.

Figure 4: Accumulated order flows and EURNOK exchange rate

(a) Financial end–users



(b) Non–financial end–users



Notes. The figure shows the NOK/EUR exchange rate (blue, left–hand axis) plotted against the accumulated Financial and Non–financial end–user order flows (red, right–hand axis) in panels a) and b) respectively from 14.05.2005 to 26.02.2021.

4.3 Correlation

Table 3 presents the correlations between the EURNOK exchange rate, the macro variables, and the order flow from the two end–user groups. "Δ" indicates a one–week change in the variable. s, p, and vix are the natural logarithm of the EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars, and the CBOE VIX, respectively. i^{diff} is the difference between Norwegian and Euro area 3–month interest rates. fin and $nonfin$ are the order flows from Financial and Non–financial end–users.

Table 3: Correlation matrix

	Δs_t	Δp_t	Δvix_t	Δi_t^{diff}	fin_t	$nonfin_t$
Δs_t	1.000					
Δp_t	-0.437	1.000				
Δvix_t	0.340	-0.275	1.000			
Δi_t^{diff}	-0.293	0.135	0.018	1.000		
fin_t	0.383	-0.182	0.092	-0.163	1.000	
$nonfin_t$	-0.310	0.181	-0.067	0.101	-0.452	1.000

Notes. The table reports the correlations between the EURNOK exchange rate, macro variables, and the net holdings in foreign currency at a weekly frequency. Δs_t, Δp_t, and Δvix_t represent the one-week change of the natural logarithm of the variables EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index from $t-1$ to t. Δi_t^{diff} is the one-week change in the interest rate differential between Norway and the Euro area. fin and $nonfin$ are the order flows from the constructed financial and non–financial end–users. The sample spans from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009).

As expected, there is a negative relationship between changes in oil price and the exchange rate. This is also true for changes in the interest rate differential. The VIX shows a positive correlation with the log change in the EURNOK exchange rate (i.e., the depreciation rate). We find that the end–user order flows are negatively correlated. Financial order flow has a positive relationship with the depreciation rate, while Non–financial flow has a negative relationship as anticipated from the plots. The findings of Bjønnes et al. (2005) suggest that the flow of the customer group that is positively correlated with the exchange rate is the active trader while the group that is negatively correlated with the exchange rate is the passive trader providing liquidity. Positive order flows imply a purchase of EUR. The NOK seems to depreciate against the EUR when the active Financial customers sell NOK and the liquidity providing Non–financial customers buy NOK. We also see that Financial customers are inclined to sell Norwegian Krone when the uncertainty in the financial market increases and to buy it when the interest differential increases. The opposite is true for Non–financial customers.

5 Empirical Analysis

In this section, we present the results of our empirical analysis. We begin by testing for stationarity of the variables. We further examine the contemporaneous relationship between the depreciation rate and macro and micro variables by estimating price impact regressions. Next, we test for cointegration. Provided that we can establish a long–run relationship, we proceed by estimating the short– and long–run coefficients in a single equation error correction model. As we discuss in Subsections 5.5 and 5.6 the results are relatively stable in different subsamples and to the inclusion of the Financial Crisis.

5.1 Testing for Stationarity

Table 4 reports the statistics and p–values of the confirmatory data analysis using the ADF test and the KPSS test in levels and first differences. The exchange rate, oil price, and volatility index are in logs. Note that because order flows by construction are differenced variables, we use the accumulated order flows to test for stationarity in levels.

Table 4: Testing for Stationarity

Variable	ADF				KPSS				I(d)
	Levels		First difference		Levels		First difference		
	Stat.	P–value	Stat.	P–value	Stat.	P–value	Stat.	P–value	
s	-1.236	0.662	-28.767***	0.000	26.434***	<0.01	0.057	>0.1	I(1)
i^{diff}	-2.625*	0.090	-19.002***	0.000	2.969***	<0.01	0.139	>0.1	I(1)
p	-2.089	0.252	-27.026***	0.000	9.576***	<0.01	0.072	>0.1	I(1)
vix	-4.629***	0.000	-33.83***	0.000	2.475***	<0.01	0.015	>0.1	I(1)
fin	-1.352	0.608	-14.143***	0.000	18.151***	<0.01	0.439*	0.060	I(1)
$nonfin$	-1.092	0.721	-12.646***	0.000	0.886***	<0.01	0.447*	0.057	I(1)

Notes. 14.10.2005 – 26.02.2021. The table reports the test statistics and p–values of the ADF and KPSS test on levels and the first differences of the variables. s, p and vix are in logs. The null for the ADF test is that the series contains a unit root. The null for the KPSS test is that the series is stationary. The lag length is based on the Bayesian (Schwarz) information criterion with a maximum of 52 lags. The model is an AR model with drift and no time trend. ***, **, * denotes rejection at the 1%, 5% and 10% levels.

In most cases, at the five percent significance level, the tests are cohesive in their conclusions. However, there are conflicting results for the VIX in level as the ADF test rejects the null hypothesis of a unit root while the KPSS test rejects the null of stationarity. For the first–difference transformation of the VIX, the conclusions coincide, and we deduce that all variables have a unit root, i.e., are non–stationary. Thus, we proceed with the analysis using the series in first differences. When testing for stationarity in the subsamples[2], we obtain similar results, and the conclusions remains unchanged. Table B.1.1 and B.1.2 in Appendix B.1 reports the results of the stationarity tests for the subsamples.

5.2 Price Impact Regressions

The relationship between the EURNOK depreciation rate and various combinations of the macro variables and customer order flows are analyzed in Table 5. We report the results of ordinary least squares (OLS) estimates of the coefficients with the one–week change in the log EURNOK exchange rate (Δs_t) as the dependent variable. "Δ" denotes a one–week change to the variables. α

[2]The first subsample is from 14.10.2005 to 03.01.2014. The last subsample is from and 10.01.2014 to 26.02.2021

is the intercept, fin_t and $nonfin_t$ are the Financial and Non–Financial order flows, p is the log of Brent Crude Oil price, vix is the log of the CBOE volatility index, and i_t^{diff} is the 3–month interest rate differential between Norway and the Euro area.

Positive estimates of coefficients entail a depreciation of the NOK against the EUR given an increase in the variable, while negative coefficients imply an appreciation. The order flow coefficients measure a one–standard–deviation change in order flow. To account for the possibility of heteroscedasticity and autocorrelation in the error terms, we estimate heteroskedasticity and autocorrelation consistent standard errors using the Newey–West procedure. The resulting t–statistics are reported in parentheses below the coefficient estimates, and the adjusted R^2 for each regression are reported in the last row. Note that this is for the full sample, excluding the Financial Crisis.

Table 5: Price impact regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.001
	(4.970)***	(1.330)	(4.562)***	(4.734)***	(1.647)*	(4.713)***	(2.019)**	(4.206)***
fin_t	0.004		0.004	0.004		0.003		0.003
	(10.136)***		(5.308)***	(7.192)***		(5.968)***		(3.913)***
$nonfin_t$		-0.004	-0.002		-0.003		-0.003	-0.001
		(-6.162)***	(-2.493)**		(-6.570)***		(-6.463)***	(-2.895)***
Δi_t^{diff}				-0.046	-0.051	-0.041	-0.045	-0.041
				(-2.244)**	(-3.014)***	(-2.634)***	(-3.444)***	(-2.678)***
Δp_t						-0.072	-0.073	-0.069
						(-5.727)*	(-7.663)*	(-5.939)*
Δvix_t						0.018	0.018	0.018
						(8.246)***	(8.889)***	(8.408)***
Adj. R^2	0.146	0.095	0.168	0.199	0.163	0.373	0.346	0.384

Notes. The dependent variable is the one–week change in the log EURNOK exchange rate from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). Δs_t, Δp_t, and Δvix_t represent the first difference of the natural logarithm of the EURNOK exchange rate, the Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index. Δi_t^{diff} is the first difference of the interest rate differential between Norway and the Euro area. Order flows are measured in EUR 100 million. The order flow coefficient measures the impact of a one–standard deviation change in the flows. "Financial" is the change in net positions of the financial customers and "Non–financial" is the change in net positions of the non–financial customers. ***, **, * denotes rejection at the 1%, 5% and 10% levels.

Depending on the specifications of the regressions, the adjusted R^2 ranges from 9.5% to 38.4%. Further, all the variables are consistently statistically significant at the five percent significance level. Financial order flow appears to account for more of the variation in the depreciation rate than the Non–financial flow. When only including either Financial (1) or Non–financial flow

(2) as regressors, both are statistically significant at conventional levels. However, the Financial flow is notably higher. The adjusted R^2 statistic is also greater for the first specification. When including both order flows in specification (3), the t–statistics of both flows drop whereas Financial order flow exhibit the highest significance of the two end–user groups. Consistent with Evans and Rime (2016) and other previous studies (e.g., Bjønnes et al. (2005); Marsh & O'Rourke, 2005) the estimated coefficients of the two customer order flows have different signs. As discussed in Subsection 4.3 this could be interpreted as the Financial customers being the active trader pushing the market, while the Non–financial customers are the passive traders being pulled by the market (Bjønnes et al., 2005).

It is important to note that when employing flow data from different end–users, one has to account for the contemporaneous correlation between the flows. In our data set, the correlation between the Financial and Non–financial end–users is -0.45. Evans and Rime (2005) find a correlation of -0.52 while Bjønnes et al. (2005) find a strong negative correlation of -0.80 in their Swedish data. Thus, none of the individual coefficients perfectly compile the price impact of the individual flow segments, and the interpretation of the coefficients does not have a structural interpretation in terms of price–impact of the orders (Evans & Lyons, 2006).

The inclusion of the change in the 3–month interest rate differential in regression (4) and (5) improves the models in terms of the adjusted R^2. The estimated coefficient is negative and significant at the five percent level. A reasonable interpretation of this result is that a higher interest rate in Norway is likely to induce investors to invest in NOK and thereby contribute to strengthening the Krone (Bergo, 2003). The coefficient remains rather stable when considering alternative specifications. On average, a 1% change in the interest rate differential corresponds approximately to a 5% change in the EURNOK exchange rate.

The adjusted R^2 increases significantly when extending the model to include all the macro variables and the separate order flows (specification (6) and (7)). The explanatory power of the equation including Financial customers (6) is higher than the equation including Non–financial customers (7). The inclusion of both order flow variables in the same equation, specification (8), yields the highest explanatory power. However, the statistical significance of both flows decreases compared to the specifications where the flows are included separately.

The change in oil price has a negative impact on the depreciation rate, implying that an increase in the oil price coincides with an appreciation of the NOK. The relationship appears economically significant in all specifications, with similar coefficients. Specifically, a 1% increase in the oil price corresponds to approximately a 0.07 % decrease in the EURNOK exchange rate on average. Since Norway is a small open economy, it is a price–taker in the oil market. It is therefore plausible that changes in the oil price serve as an exogenous term–of–trade shock to the Norwegian economy resulting in exchange rate appreciation due to higher commodity prices (Bernhardsen and Røisland, 2000; Ferraro et al., 2015).

The positive relationship between changes in the VIX and the EURNOK exchange rate indicates a depreciation of the currency, given turmoil in the financial market. The fact that the coefficient is highly significant substantiates the assertion of Bernhardsen and Røisland (2000) that the currency of a small country like Norway is likely to depreciate in times of turbulence. Since the VIX is a measure of expected volatility and risk appetite of the market participants (Kohlscheen et al., 2016), one would expect an increase in the indicator to be associated with an appreciation of a safe haven currency (Flatner, 2009). The NOK can be regarded as relatively illiquid compared to the EUR, making it unattractive to investors during uncertain times. The results indicate that a 1% increase in the VIX coincides with a 0.02% depreciation of the Norwegian Krone against the EUR.

5.3 Testing for Cointegration

This section examines whether the log exchange rate is cointegrated with the accumulated flows, before extending the cointegrating analysis to include the macro variables. It is plausible that there exists a long–run relationship between order flows and the exchange rate. According to Rime and Solji (2006), the effect of order flow has to be permanent. The exchange rate must be a function of cumulative order flows, and thus, exchange rates and cumulative order flows should be cointegrated. Several studies within the microstructure literature use a cointegration methodology. For instance, both Bjønnes et al. (2005) and Chinn and Moore (2011) use the Johansen cointegration procedure to investigate whether there is a long–term relation between accumulated flows and the exchange rate.

We apply the Johansen procedure and the Engle–Granger cointegration test to check for cointegration between the exchange rate, cumulative order flows, and the macroeconomic fundamentals (see Appendix A.2 for a description of the tests). We evaluate four Vector Autoregressive (VAR) models: two containing the exchange rate and the separate cumulative order flows, and two that additionally include the interest rate differential and the natural logarithm of the oil price and the VIX. The lag length is determined based on Schwarz's Bayesian information criterion (SBIC). Table 6 reports the results of the cointegrating analysis for the Financial– and Non–financial order flows and the log spot EURNOK exchange rate. The lag length is fixed at two lags for both VARs.

Table 6: Testing for Cointegration and cum. order flow

Panel A: Johansen cointegration test

	Financial		Non–financial	
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	48.780**	0.001	8.819	0.756
$r = 1$	3.454	0.565	1.457	0.881

Panel B: Engle–Granger cointegration test

ADF	-4.960***	0.001	-2.355	0.594

Notes. 14.10.2005 – 26.02.2021. The table shows cointegration tests for the Financial and Non–financial order flows and the log spot EURNOK exchange rate. Panel A reports the Johansen Trace statistics of cointegration ranks 0 and 1 and allows for a linear trend in the data. Panel B reports the test statistics and p–values of the ADF test on the residuals of the cointegrating regression. ***, **, * denotes rejection at the 1%, 5% and 10% levels respectively in both panels. The lag selection is based on the Bayesian (Schwarz) information criterion with an optimal lag length of two for all cases.

Panel A presents the Johansen Trace statistics from the two VARs after being transformed into VECMs. The null of no cointegrating ranks is rejected for Financial flow, but the statistic does not provide evidence against the null hypothesis for the Non–financial flow. Panel B shows the Engle–Granger cointegration test. It tests the residuals from a single–equation cointegrating regression with log EURNOK as the dependent variable (i.e., $s_t - \hat{\gamma} x_t$, where x is the cumulative flows from the two end–users in the VECM). We use an ADF test to assess if unit roots are present. The residuals will be stationary if the time series are cointegrated. The results indicate that the error correction term is stationary for the Financial flow and non–stationary for the Non–financial flow. In combination, Panels A and B suggest a long–term relation between Financial end–user order flows (accumulated) and the exchange rate; however, there is no evidence of cointegration between Non–financial flow and the exchange rate.

Table 7 shows the cointegration tests for the hybrid model where oil price, VIX, and the interest rate differential are included in the cointegrating systems. At the five percent significance level, we find evidence of three cointegrating ranks in the VECM containing Financial flow and one cointegrating rank in the VECM containing Non–financial flow. However, in Panel B, when testing the single–equation cointegrating regression with the exchange rate as the dependent variable (i.e., $s_t - X_t\hat{\Gamma}$, where X is a vector containing cumulative flows from the two end–users and the macro fundamentals in the VECM), only the estimated error–correction term, including Financial flow, is stationary.

Table 7: Testing for Cointegration – Exchange rate, cum. order flow and macro variables

	Financial		Non–financial	
Panel A: Johansen cointegration test				
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	184.1681***	0.001	93.798***	0.002
$r = 1$	83.021***	0.001	50.618*	0.098
$r = 2$	39.119**	0.018	24.619	0.456
$r = 3$	19.550	0.063	9.015	0.734
$r = 4$	4.095	0.468	1.811	0.815
Panel B: Engle–Granger cointegration test				
ADF	-7.000***	0.000	-3.897	0.304

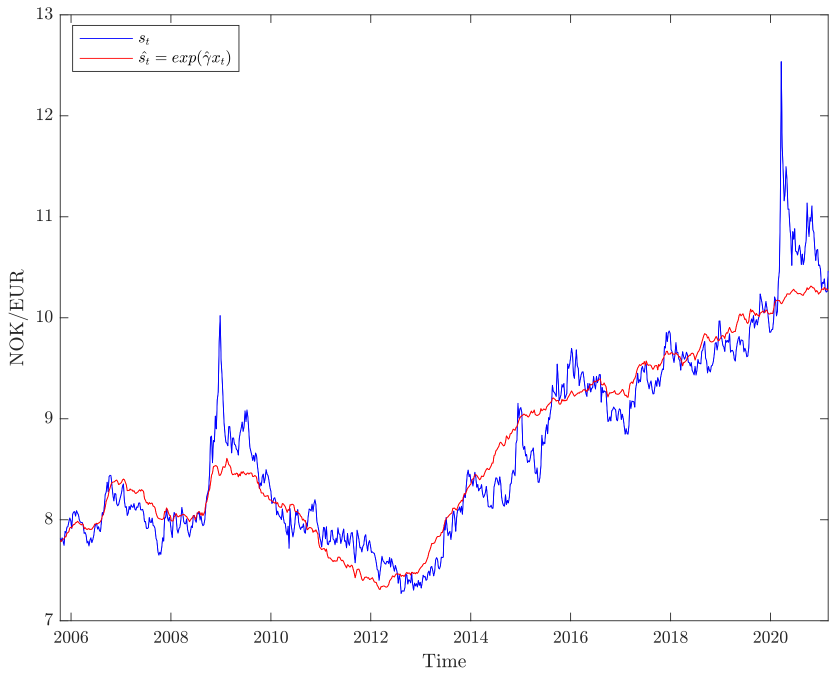
Notes. 14.10.2005 – 26.02.2021. The table shows cointegration tests for the Financial and Non–financial order flows and the log spot EURNOK exchange rate, oil price, VIX, and the interest rate differential. Panel A reports the Johansen Trace statistics of cointegration ranks 0 and 4 and allows for a linear trend in the data. Panel B reports the test statistics and p–values of the ADF test on the residuals of the cointegrating regression with log spot exchange rate as the dependent variable. ***, **, * denotes rejection at the 1%, 5% and 10% levels respectively in both panels. The lag selection is based on the Bayesian (Schwarz) information criterion with an optimal lag length of two for all cases.

Like Evans and Rime (2016) we establish a long–run relation between Financial end–user order flow and the EURNOK exchange rate. We do, however, struggle to find evidence of cointegration for both models (i.e., the micro– and hybrid model) when including Non–financial order flow in the models. A feasible explanation for this result might be that even though reporting banks usually only provide short–term liquidity and seldom take large overnight positions, we observe changes in the accumulated flows of the reporting banks in our data. This finding might affect the relationship between the exchange rate and the order flow of the Non–financial customers in terms of being overnight liquidity providers. Based on the resulting conclusions from Table 6 and 7 we proceed with the analysis using only Financial flow in our model. To verify the results, we also test for cointegration between the variables in the subsamples. The conclusions remain the same. The results are reported in Table B.2.1 – B.2.2 in Appendix B.2.

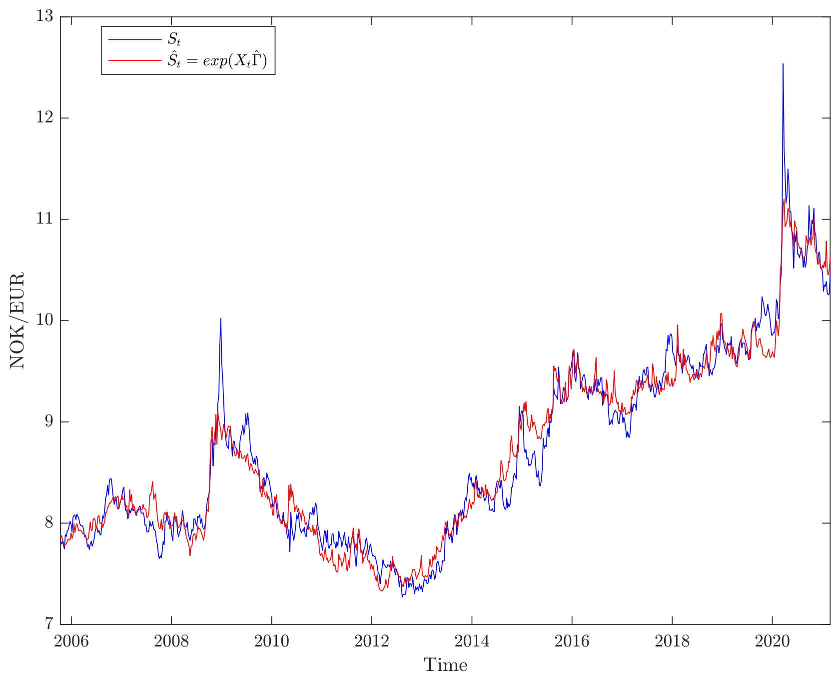
Figure 5 depict visual evidence of the long–lasting effects the variables have on the EURNOK exchange rate (assuming weak exogeneity of the variables for the cointegrating vector). Panel a) in Figure 5 plots the EURNOK rate, s_t, against the fitted value, $\hat{s_t} = exp(\hat{\gamma} x_t)$, estimated from the cointegrating relation including Financial order flow, while Panel b) plots it against that of the hybrid model, $\hat{s_t} = exp(X_t \hat{\Gamma})$. Here x is cumulative order flow, and X is a vector of the macro fundamentals and cumulative order flow. It is apparent that the long swings experienced by the exchange rate are linked to the variations in Financial flow, which is consistent with the findings of Evans and Rime (2016). The link is even tighter when we include the macro variables in the cointegrating regression.

Figure 5: Long–lasting effects

(a) NOK/EUR s_t and cointegrated accumulated Financial order flow.



(b) NOK/EUR s_t and cointegrated accumulated Financial order flow and macro variables.



Notes. Panel a) shows the NOK/EUR exchange rate, s_t (blue) plotted against an estimate of the cointegrating relation with cumulative Financial order flow, $\hat{s_t} = exp(\hat{\gamma} x_t)$ (red). Panel b) shows the NOK/EUR exchange rate, s_t (blue) plotted against an estimate of the cointegrating relation with cumulative Financial order flow and the macro variables, $\hat{s_t} = exp(X_t \hat{\Gamma})$ (red) .

5.4 Error Correction Models

Section 5.3 confirms that there exist a long–run relationship between the exchange rate and accumulated Financial flow in both a micro–and hybrid system. Thus, we proceed by estimating two single–equation error correction models (assuming weak exogeneity). This provides us with estimates of the short– and long–run relationship between changes in the exchange rate and the cointegrated variables. Focusing on the exchange rate regression, we include the estimated error–correction terms from the cointegrating analysis in both regressions. Since the data covers the Financial Crisis, we exclude the observations from July 2008 to June 2009. This is consistent with Evans and Rime (2016), and by considering Figure 1 – 4 it is apparent that the time series characteristics of the variables are highly atypical.

Like Bjønnes et al. (2005) we use a Generalized Method of Moments (GMM) procedure to account for overlapping observations and the fact that the standard errors will be serially correlated when studying changes beyond one week. We obtain standard errors that are robust to heteroskedasticity and autocorrelation using the Newey–West estimator. The weighting matrix contains the exogenous variables of the regression, and the lag length is automatically chosen using SBIC with a maximum of 52 lags.

Table 8: ECM – Full sample excl. the Financial Crisis

	1 week		4 weeks		12 weeks	
	(1)	(2)	(1)	(2)	(1)	(2)
α	0.002	0.001	0.005	0.004	0.010	0.010
	(3.956)***	(3.986)***	(3.263)***	(2.817)***	(2.107)**	(3.135)***
fin_t	0.004	0.003	0.008	0.006	0.013	0.009
	(9.683)***	(5.763)***	(7.909)***	(4.430)***	(4.681)***	(4.414)***
Δi_t^{diff}		-0.044		-0.036		-0.036
		(-2.629)***		(-5.647)***		(-3.047)***
Δp_t		-0.069		-0.074		-0.053
		(-5.919)***		(-3.834)***		(-3.950)***
Δvix_t		0.019		0.025		0.029
		(8.671)***		(4.259)***		(5.149)***
EC_{-n}	-0.064	-0.111	-0.206	-0.299	-0.490	-0.616
	(-4.162)***	(-3.756)***	(-4.229)***	(-3.982)***	(-6.080)***	(-6.817)***
Adj. R^2	0.171	0.412	0.283	0.571	0.427	0.688

Notes. The table presents GMM regressions where the dependent variable is the one, four, and twelve–week change in the log EURNOK exchange rate (log(NOK/EUR_t) - log(NOK/EUR_{t-n})). Here n denotes the number of weeks the return is measured over. The sample spans from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). Δs_t, Δp_t, and Δvix_t represent the change of the natural logarithm of the variables EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index for $t - n$ to t. Δi_t^{diff} is the change in the interest rate differential between Norway and the EU. Financial order flow is the change in net positions of the financial customers and is measured in EUR 100 million. The order flow coefficient measures the impact of a one–standard deviation change in the flow. EC_{-n} is the error correction term from the cointegration analysis, lagged with n periods. The regressions are estimated using weekly data and overlapping observations using GMM. The weighting matrix contains the exogenous variables. Standard errors are robust, measured with Newey–West HAC procedure. Statistical significance at the 1, 5, and 10 percent level is denoted by "***", "**" ,and "*" respectively.

The ECM regressions of changes in the exchange rate on contemporaneous flow and changes to the macro variables are reported in Table 8 for the 1–week, 4–week, and 12–week horizon. By extending the horizon, it allows us to investigate the persistence of the price effects (Lyons, 2003). In all cases, the error correction terms' estimated coefficient is negative and statistically significant at the one percent significance level. As it measures the speed of adjustment back to the long–run equilibrium level, the negative sign implies that the adjustment is in the correct direction. This result indicates that the EURNOK exchange rate reverts to a conditional mean, affirming a long–term linear relation (Chinn & Moore, 2011). The absolute size of the error correction term coefficient and t–statistic increases when the macro variables are included in the cointegrating relation and when the horizon is extended. For instance, at the 1–week horizon, 6.4% of the adjustment takes place each period for the micro–model and 11.1% for the hybrid model. When extending the horizon to 12 weeks, the speed of adjustment over the period increases to 49% and 61.6%, respectively.

The signs of all variables are consistent for both regressions at all horizons. The coefficient of the Financial flow is positive and statistically significant with a slightly higher estimate for the micro model. Comparing the numbers from the hybrid model to the findings of Bjønnes et al. (2005) we see a similar pattern of economic significance. At the 4–week horizon, the standard deviation for changes in the exchange rate is 2.12%. A one–standard deviation increase in the Financial flow (i.e., 2.046 billion EUR) implies an increase in the EURNOK exchange rate of 0.61% on average. In comparison, they find that a one–standard deviation increase in the net flow of Financial customers will, on average, imply an increase in the EURSEK exchange rate of 0.66% and the standard deviation of the exchange rate over a 30–day horizon is 2.33%.

Contrary to their results, we do not observe any evidence of an increase in the coefficient of the Financial flow when extending the horizon (recall that the reported order flow coefficient in Table 8 measures the impact of a one–standard deviation change to the variable). Rather, the coefficient size is relatively stable over all horizons with a moderate decrease in both the coefficients and the t–statistics. We are thus unable to draw the same inference as Bjønnes et al. (2005) and Evans and Lyons (2012) that it takes more than a quarter for all information contained in order flow to be impounded in the exchange rate.

Changes in the 3–month interest rate differential and the oil price have negative and statistically significant coefficients at all horizons. The signs are consistent with the findings in Subsection 5.2, and thus the discussion still applies. An increase in the oil price is expected to be followed by higher export revenues (Kohlscheen et al., 2016). A higher Norwegian interest rate is likely to induce investors to invest in Norway (Bergo, 2003). Thus, as the demand for the Norwegian Krone increases, the currency appreciates. The VIX also exhibits results coherent with Subsection 5.2. The positive coefficient indicates a depreciation of the NOK, given an increase in financial uncertainty. Overall, the findings imply that changes in the oil price, interest rate differential, and the VIX are important drivers for the EURNOK exchange rate. There are no notable changes nor tendencies in the economic significance of the variables over the different horizons. In absolute value, as the horizon increases, the coefficient decreases moderately for the interest rate differential and increases for the VIX. At the same time, we observe the highest coefficient at the 4–week horizon and the lowest at the 12–week horizon for the oil price.

The explanatory power of the regressions ranges between 17–69%. The results indicate strong evidence of a long–run relationship between the exchange rate and the accumulated Financial order flow augmented by the macro variables. When allowing the macro variables to enter contemporaneously and in the long–run relationship, the error correction specifications explain a greater proportion of the variation in the EURNOK exchange rate. Consistent with previous studies, the explanatory power also increases substantially when increasing the horizon (e.g., Bjønnes et al. (2005); Evans and Lyons (2012); Lyons (2003)).

5.5 Robustness – Stability Analysis

In order to examine the robustness of the results reported in Section 5.4, we divide the full sample into two subsamples to assess the stability of the relations. The first sample corresponds to Evans and Rime's (2016) sample from October 2005 to December 2013, excluding the Financial Crisis. The second sample is the remaining half of our data set, from January 2014 to February 2021. The results are reported in Panel A and B in Table 9. Overall, the results appear relatively stable, yet we observe some noteworthy differences that should be recognized. The error correction term is negative and statistically significant for both subsamples at all horizons, although somewhat lower in the first sample. The sign of the order flow coefficient is consistently positive, while it is less significant in the last sample compared to the first and full sample. Still, the coefficients are comparable to those obtained in the initial analysis.

The most notable discrepancies are observed in the explanatory power of the specifications and the estimated coefficients and statistics of the macro variables. When evaluating the micro model (1), diagnostics for both the full sample and the last sample are inferior at all horizons compared to the first sample. For instance, at the 1–week horizon, the adjusted R^2 for the first and last sample are 31.1% and 11.7%, respectively. However, in specification (2) when including the macro variables, the explanatory power are more comparable across subsamples and horizons. The second notable feature is that the oil price and VIX exhibit higher coefficients in absolute value in the last sample compared to the first sample. Specifically, the magnitude of the coefficients and the t–statistics of the oil price indicate that changes in the oil price significantly impact variations in the exchange rate in the last sample. The oil price is not even statistically significant at any conventional significance level in the first sample at the 4– and 12–week horizon.

Figure 1 – 3 reveal clear signs of increased volatility in the macro variables during both the Financial Crisis and the ongoing COVID–19 pandemic. Without going further into the pandemic's uncharted aspects, it is worthwhile to investigate the effect of excluding observations from the pandemic (from and

Table 9: ECM – First and last sample

	1 week		4 weeks		12 weeks	
	(1)	(2)	(1)	(2)	(1)	(2)
			Panel A: First sample			
α	0.002	0.002	0.004	0.005	0.009	0.010
	(3.472)***	(4.143)***	(2.351)**	(3.403)***	(1.868)*	(3.603)***
fin_t	0.005	0.004	0.009	0.007	0.016	0.011
	(9.597)***	(8.092)***	(6.793)***	(5.297)***	(4.634)***	(4.955)***
Δi_t^{diff}		-0.022		-0.045		-0.052
		(-3.586)***		(4.827)***		(-5.799)***
Δp_t		-0.031		-0.019		-0.007
		(-2.950)***		(-1.091)		(-0.452)
Δvix_t		0.015		0.022		0.023
		(5.768)***		(5.272)***		(3.574)***
EC_{-n}	-0.061	-0.082	-0.185	-0.243	-0.388	-0.564
	(-3.566)***	(-4.275)***	(-2.625)***	(-3.596)***	(-2.957)***	(-5.821)***
Adj. R^2	0.311	0.389	0.433	0.562	0.551	0.706
			Panel B: Last sample			
α	0.002	0.001	0.006	0.004	0.017	0.011
	(2.554)**	(1.780)*	(2.520)**	(2.204)**	(2.148)**	(2.291)**
fin_t	0.004	0.002	0.008	0.005	0.011	0.006
	(4.419)***	(3.712)***	(4.313)***	(3.102)***	(3.760)***	(2.411)***
Δi_t^{diff}		-0.078		-0.025		-0.014
		(-2.849)***		(-3.420)***		(-1.985)**
Δp_t		-0.082		-0.098		-0.074
		(-8.190)***		(-6.270)***		(-5.470)***
Δvix_t		0.022		0.024		0.032
		(7.439)***		(3.785)***		(4.991)***
EC_{-n}	-0.098	-0.197	-0.319	-0.465	-0.747	-0.883
	(-4.714)***	(-3.037)***	(-4.495)***	(-3.744)***	(-5.654)***	(-8.120)***
Adj. R^2	0.117	0.494	0.267	0.659	0.485	0.738

Notes. The table presents GMM regressions where the dependent variable is the 1–, 4–, and 12–week change in the log EURNOK exchange rate (log(NOK/EUR_t) - log(NOK/EUR_{t-n})). Here n denotes the number of weeks the return is measured over. In Panel A, the sample spans from 14.10.2005 to 03.01.2014, excluding the Financial Crisis (July 2008 to June 2009). In Panel B, the sample spans from 10.01.2014 to 26.02.2021. Δs_t, Δp_t, and Δvix_t represent the change of the natural logarithm of the variables EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index for $t-n$ to t. Δi_t^{diff} is the change in the interest rate differential between Norway and the EU. Financial order flow is the change in net positions of the financial customers and is measured in EUR 100 million. The order flow coefficient measures the impact of a one–standard deviation change in the flow. EC_{-n} is the error correction term from the cointegration analysis, lagged with n periods. The regressions are estimated using weekly data and overlapping observations using GMM. The weighting matrix contains the exogenous variables. Standard errors are robust, measured with Newey–West HAC procedure. Statistical significance at the 1, 5, and 10 percent level is denoted by "***", "**", and "*" respectively.

including January 2020). In Table B.3.1 in Appendix B.3 we report ECM regressions using data from January 2014 to December 2019. We observe a higher explanatory power for the micro model at all horizons and somewhat lower for the hybrid model compared to Panel B. Further, the oil price coefficient and its significance decreases. According to Akram (2004), the negative correlation between the Norwegian exchange rate and the oil price strengthens when oil price fluctuations are outside the normal range, especially with falling oil prices and when the probability of low oil prices increases. Such tendencies characterize the period from January 2020 until now and could accordingly explain the higher coefficient and significance of changes in the oil price. However, the majority of the conclusions drawn from the main analysis are still valid for each subsample.

5.6 Robustness – The Effect of the Financial Crisis

Panel A and B in Table 10 shows the results from the ECM regressions estimated when including the Financial Crisis (July 2008 to June 2009) in the first sample and the full sample. The inclusion does not alter the signs of the coefficients, and their magnitude remains relatively stable for most variables. However, we observe an increase in the significance of the oil price in the first sample, perhaps due to the extreme decline in oil prices in 2009. This finding is in line with the discussion above regarding non–linearities in the relationship between oil prices and the Norwegian exchange rate argued by Akram (2004). The most significant difference is the decline in the explanatory power of the micro model (1) for the first sample at the 1– and 4–week horizon when including the Financial Crisis. Overall, the changes in the explanatory power are minor in all samples. To conclude, the impact of including the Financial Crisis does not seem to alter the main inferences drawn from the analysis.

Table 10: ECM – First and full sample incl. the Financial Crisis

	1 week		4 weeks		12 weeks	
	(1)	(2)	(1)	(2)	(1)	(2)
	Panel A: First sample including the Financial Crisis					
α	0.002	0.001	0.005	0.004	0.015	0.012
	(3.208)***	(3.377)***	(2.507)**	(3.563)***	(2.140)**	(4.742)***
fin_t	0.005	0.004	0.008	0.005	0.022	0.011
	(6.175)***	(4.355)***	(2.952)***	(2.834)***	(3.693)***	(4.896)***
Δi_t^{diff}		-0.028		-0.056		-0.056
		(-6.698)***		(-3.794)***		(-7.613)***
Δp_t		-0.046		-0.037		-0.051
		(-2.509)**		(-1.850)*		(-3.227)***
Δvix_t		0.013		0.022		0.027
		(3.658)***		(4.791)***		(4.008)***
EC_{-n}	-0.059	-0.100	-0.223	-0.348	-0.407	-0.620
	(-1.863)*	(-4.987)***	(-2.906)***	(-3.726)***	(-2.775)***	(-6.330)***
Adj. R^2	0.185	0.366	0.281	0.575	0.541	0.703
	Panel B: Full sample including the Financial Crisis					
α	0.002	0.001	0.005	0.004	0.014	0.011
	(4.033)***	(3.800)***	(3.115)***	(2.794)***	(2.412)**	(3.628)***
fin_t	0.004	0.003	0.009	0.004	0.014	0.009
	(7.501)***	(5.359)***	(4.329)***	(3.119)***	(3.920)***	(5.101)***
Δi_t^{diff}		-0.035		-0.047		-0.040
		(-4.052)***		(-4.539)***		(-3.778)***
Δp_t		-0.068		-0.047		-0.058
		(-5.768)***		(-4.616)***		(-4.804)***
Δvix_t		0.018		0.025		0.029
		(7.858)***		(4.432)***		(4.926)***
EC_{-n}	-0.061	-0.110	-0.214	-0.346	-0.462	-0.631
	(-3.325)***	(-4.494)***	(-4.316)***	(-4.515)***	(-5.539)***	(-6.915)***
Adj. R^2	0.137	0.395	0.238	0.570	0.443	0.736

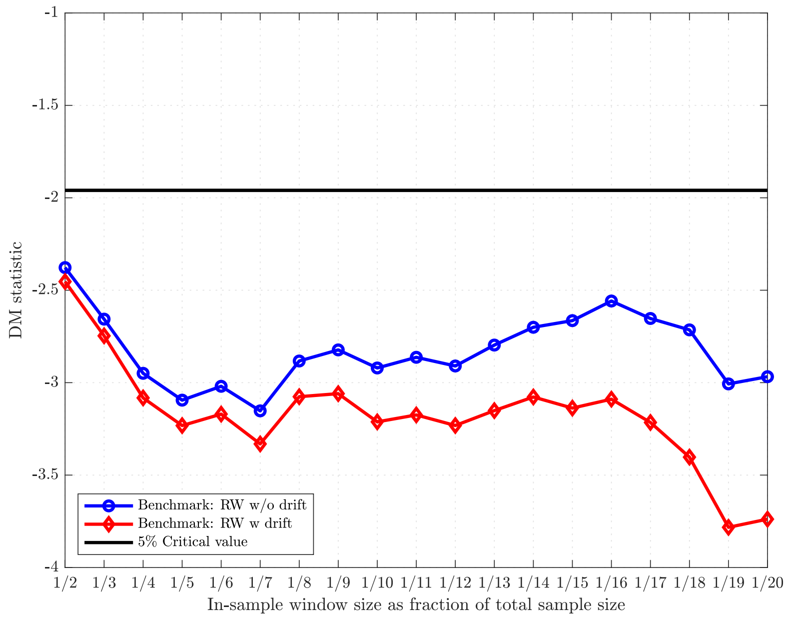
Notes. The table presents GMM regressions where the dependent variable is the 1–, 4–, and 12–week change in the log EURNOK exchange rate (log(NOK/EUR_t) - log(NOK/EUR_{t-n})). Here n denotes the number of weeks the return is measured over. In Panel A, the sample spans from 14.10.2005 to 03.01.2014. Panel B spans from 14.10.2005 to 26.02.2021. Both samples include the Financial Crisis (July 2008 to June 2009). Δs_t, Δp_t, and Δvix_t represent the change of the natural logarithm of the variables EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index for $t-n$ to t. Δi_t^{diff} is the change in the interest rate differential between Norway and the EU. Financial order flow is the change in net positions of the financial customers and is measured in EUR 100 million. The order flow coefficient measures the impact of a one–standard deviation change in the flow. EC_{-n} is the error correction term from the cointegration analysis, lagged with n periods. The regressions are estimated using weekly data and overlapping observations using GMM. The weighting matrix contains the exogenous variables. Standard errors are robust, measured with Newey–West HAC procedure. Statistical significance at the 1, 5, and 10 percent level is denoted by "***", "**", and "*" respectively.

5.7 Robustness – Out–of–Sample Fit Performance

In this section, we examine the predictive ability of the models by comparing their performance relative to the random walk benchmark. This method is not a true out–of–sample forecast but rather an out–of–sample fit exercise since we use the realized values of the contemporaneous regressors. It is thus an ex–post forecast used to evaluate the predictive content of the variables inspired by Ferraro et al. (2015). This is a common technique suggested by Meese and Rogoff (1983) as a criterion when evaluating exchange rate models. Note that we have estimated the cointegrating vector over the entire sample, so only the short–run dynamics are treated as time–varying while the long–run relationship is not. We do this because we want to obtain estimates of the cointegrating relationship with as much information as feasible. This procedure is also done in other studies like MacDonald and Taylor (1993).

Following the methodology of Ferraro et al. (2015), we estimate the coefficients of the model using a rolling in–sample window to generate a set of one–step–ahead pseudo out–of–sample forecasts. We use varying in–sample windows measured as fractions of the total sample size. First, the forecasts are compared to those implied by the random walk, both with and without a drift. Then, using the Diebold and Mariano (1995) test of equal predictive ability, we evaluate the model against the two benchmarks by comparing the Mean Squared Forecast Errors (MSFEs) (See Appendix A.3 for a description of the test). When the Diebold and Mariano (DM) test statistic is negative, it implies that the model outperforms the benchmark forecasts. When the test statistic is below -1.96, it forecasts significantly better at the five percent significance level. Figure 6 shows the DM test statistic for the hybrid model at the 1–week horizon. The x–axis reports the window–size relative to the sample size.

Figure 6: Diebold and Mariano (1995) test – Hybrid model

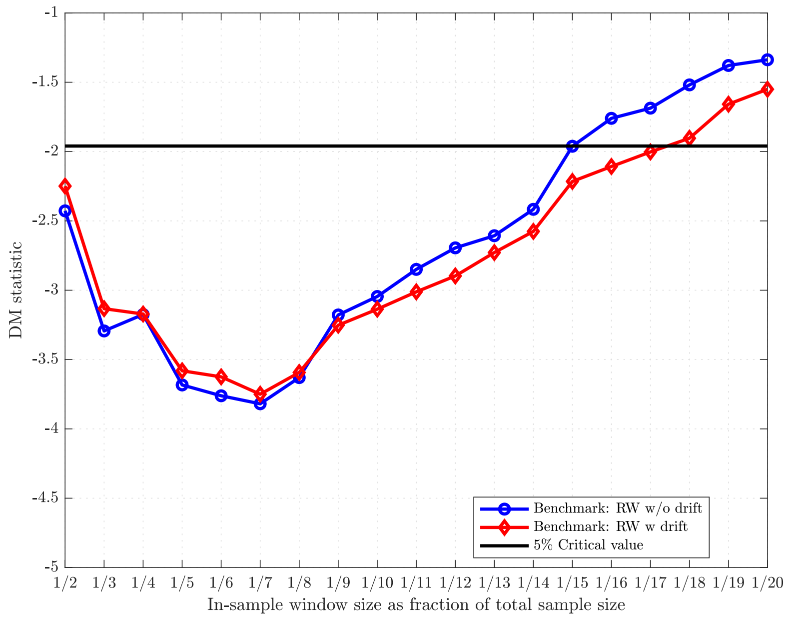


Notes. The figure plots the Diebold and Mariano (1995) test statistic when comparing the hybrid ECM model (2) to a random walk with (circles) and without (diamonds) drift for varying in–sample window sizes (x–axis) at a 1–week horizon. The window size is reported as fractions of the sample size. The sample spans from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). The black line is the DM test statistic's critical value, and negative values imply that the model outperforms the benchmark. When the statistics are lower than the critical value, it performs significantly better at the five percent significance level.

Regardless of the in–sample window–size the model outperforms the predictions of both benchmarks. The statistic increases with the window size, but overall, we conclude that the model presents highly robust results compared to the benchmarks. For comparison, we also plot the DM test statistics of the micro model in Figure 7. The model forecasts better than the benchmarks at all window–sizes. However, we can only reject the null of equal predictive ability for window–sizes larger than 1/15 of the sample.

When comparing our results from the Diebold and Mariano (1995) test to the Clark and West (2006) test of equal predictive ability, we see clear indications

Figure 7: Diebold and Mariano (1995) test – Micro model



Notes. The figure plots the Diebold and Mariano (1995) test statistic when comparing the micro ECM model (1) to a random walk with (circles) and without (diamonds) drift for varying in–sample window sizes (x–axis) at a 1–week horizon. The window size is reported as fractions of the sample size. The sample spans from 14.10.2005 to 26.02.2021, excluding the Financial Crisis (July 2008 to June 2009). The black line is the DM test statistic's critical value, and negative values imply that the model outperforms the benchmark. When the statistics are lower than the critical value, it performs significantly better at the five percent significance level.

of robustness (See Appendix A.4 for description). Thus, the Clark and West test only strengthens the results. The statistics and p–values of the Clark and West test for both models are reported in Table B.4.1 in Appendix B.4. The tests are not able to tell us much about the actual forecasting ability of the models. However, they affirm that the out–of–sample fit of both models is pretty good and that the hybrid model seems to beat the micro model in this simple exercise.

6 Conclusion

This thesis examines the relationship between the EURNOK exchange rate, macroeconomic fundamentals, and end–user order flows at a weekly frequency. Specifically, we analyze the variations in the exchange rate using the differential between the 3–month interest rates in Norway and the Euro area, Brent Crude Oil price, the CBOE volatility index, and order flows for the period 2005 to 2021. Further, we utilize the fact that Norges Bank provides us with a detailed dataset classifying order flows according to customer type, and transactions according to the contract type. In our thesis, we distinguish between Financial and Non–financial end–users, enabling us to address the heterogeneous relationships between the end–users and the depreciation rate. The results confirm the findings of, along with others, Bjønnes et al. (2005) and Evans and Rime (2016) that different customer types exhibit different correlations with exchange rates.

The key results of our analysis are quite comparable to previous literature within the field. The explanatory power of the Financial end–users exceeds that of the Non–financial end–users when both flows are included in the specification of the price impact regression. The inclusion of the macro variables elevates the explanatory power substantially. For the hybrid models containing all macro variables and the order flows, the adjusted R^2 ranges between 35–38%. In comparison, the regressions only including the end–user order flow yields a maximum of 17%. Further, we find a statistically significant positive relationship between the Financial end–users and the depreciation rate and a negative relationship between the Non–financial end–users. This is consistent with the findings of Bjønnes et al. (2005) and Evans and Rime (2016). It indicates that the Financial customers are the active traders, and the Non–financial customers are passive traders providing liquidity. Both a change in the interest rate differential and the oil price has an adverse effect on the depreciation rate. At the same time, financial uncertainty is positively correlated with a change in the exchange rate.

We establish a long–run relation between cumulative Financial order flow and the exchange rate. However, we cannot draw the same conclusion using Non–financial flow. Similarly, in combination with the macro variables, only the hybrid model containing Financial flow shows evidence of cointegration in a single–equation regression with log EURNOK as the dependent variable. Comparing the micro–ECM to the hybrid–ECM, we observe that the model augmented by the macro fundamentals has a substantially higher explanatory power. The explanatory power increases over the horizon for both models at the 1–week, 4–week, and 12–week horizon.

The key results are relatively stable over time. Thus, the hybrid model still outperforms the micro model. However, the first sample exhibits a notably higher explanatory power for the micro model compared to the full and the last sample. The change in oil price exhibits a significant and strong coefficient in both the full and last sample, yet it is insignificant in the first subsample. We observe an increase in the significance of the oil price when including the observations from the Financial Crisis in the first sample. This result might be due to the extreme decline in oil prices observed in 2009 and is in line with Akram (2004) and his evidence of a non–linear negative relationship between the value of the Norwegian Krone and crude oil prices. This argument is supported as the significance of oil price decreases when excluding the COVID–19 pandemic. We also examine the out–of–sample fit of the two models in terms of their ability to forecast future changes in the EURNOK exchange rate. Comparing their forecasting abilities to the random walk benchmarks, both models have lower Mean Squared Forecast Errors. Nevertheless, it is apparent that the hybrid model also outperforms the micro model.

In general, our results support previous findings of order flows being essential drivers of movements in the exchange rate. Further, we find that a hybrid model is superior to the other specifications. We also find evidence that there might exist a non–linear relationship between the Krone and oil prices. Consequently, it could be interesting to investigate this relationship further over the same sample as it might alter our conclusion that the oil price effects are unstable. Additionally, several extensions can be included in our applied model and analysis. One possible extension is to include other currencies to analyze if the results are persistent beyond the EURNOK relationship. Further, it would be interesting to explore the information conveyed by other end–users and macro variables to see if the explanatory power for changes in the exchange rate is more substantial than what we obtain in our thesis.

Appendices

Appendix A Econometric Theory

A.1 *Stationarity*

Many time series techniques rely on the assumption that the data is stationary. Brooks (2014) defines a stationary series as a series with a constant mean, constant variance and constant autocovariance for each given lag, i.e. the series does not have any trends or seasonality. Determining whether a series is stationary or not is important and will influence the behavior and properties of the time series. Shocks to a stationary variable will diminish whereas a shock to a non–stationary variable will persist. Non–stationarity can lead to spurious regressions that regressions that are worthless even though they look good. A non–stationary series is integrated of order d and must be differenced d times to induce stationarity. This can be expressed as $y_t \sim I(d)$ and implies that the series contains d unit roots (Brooks, 2014).

In order to test the time series for stationarity, we use the augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The ADF test is a unit root test which examines the null hypothesis that the time series contains a unit root. The KPSS test is a stationarity test because it has stationarity in the null hypothesis. By comparing the results of both tests, we can evaluate the robustness of the conclusions. The tests are defined as:

ADF	KPSS
$H_0 = y_t \sim I(1)$	$H_0 = y_t \sim I(0)$
$H_1 = y_t \sim I(0)$	$H_1 = y_t \sim I(0)$

Both tests are sensitive to construction. Information criteria can be used to determine the optimal lag length by minimizing the value subject to the number of parameters. There are various information criteria which differ in computation of the penalty term. The most common information criteria are the Akaike– (AIC), the Scwarz's Bayesian– (SBIC), and the Hannan–Quinn (HQIC) information criterion (Brooks, 2014). No one of these are clearly superior to the other and thus, it is common to consider all of them to decide on the optimal lag length.

A.2 *Cointegration*

A set of variables are cointegrated if a linear combination of them is stationary (Brooks, 2014). The variables move together over time indicating that there exists a long–term relationship between the variables. The variables might deviate from their relationship in the short term, but their long run association will be present. Several methods can be used for estimation of parameters in cointegrated systems, we applied the Engle–Granger 2–step method and the Johansen method.

The Engle–Granger method is a two–step procedure. The first step is to confirm that all variables are $I(1)$. If unit roots are present you proceed by estimating the cointegrating regression using OLS. From the regression the residuals are saved and tested for the presence of unit roots. This can be determined by using an ADF test. If the time series is cointegrated, the residuals will be stationary $I(0)$. The second step is to use the residuals obtained in the first step in an error correction model.

Following the description outlined in Brooks (2014), the Johansen method is a procedure for testing if there exists a cointegrated relationship between several non–stationary time series. As opposed to the Engle–Granger method it is a systems approach capable of establishing more than one cointegrating relationship. Given a set of two or more variables g that are $I(1)$, a VAR model containing these variables is constructed with k lags. The VAR is transformed into a VECM which is a VAR in first differences and $k-1$ lags of the dependent variables g

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t$$

where $\Pi = (\sum_{i=1}^{k} \beta_i) - I_g$ and $\Gamma_i = (\sum_{j=1}^{i} \beta_j) - I_g$. Focusing on the matrix of long–run coefficients, Π, the test examines the rank of the matrix through its eigenvalues. The rank of Π will not be significantly different from zero if the variables are not cointegrated. The Johansen test has two statistics, the Trace statistic and the Maximum Eigenvalue statistic. We use the Trace test in our thesis. It is a joint test which examines the number of linear combinations in the time series. The test is defined as; $H_0 : Rank(\Pi) \leq r$, where r is the number of cointegrating vectors under the null ($\leq g$). Π cannot be of full rank (g) as it would imply that the original y_t is stationary. If it has zero rank there is no cointegrating relationship. The test is sequential, starting with $H_0 : r = 0$ vs. $H_1 : 0 < r \leq g$. If the null is not rejected, the conclusion would be that there are no cointegrating vectors. On the contrary, if the null hypothesis is rejected, we know there exists at least one cointegrated vector and you proceed by testing for $r = 1$. This continues until the null–hypothesis is not rejected (Brooks, 2014, p. 388).

A.3 *Diebold and Mariano Test*

The Diebold and Mariano (1995) test compares the predictive accuracy of two forecasts. With a set of actual values, y_t, and two sets of forecasts, $\hat{y}_{1t}$ and $\hat{y}_{2t}$ for $t = 1, \ldots, T$, they ask whether the forecasts are equally good.

The test evaluates the forecast errors of the forecasts of the structural model and those of the benchmark. By defining the forecast errors as $e_{it} = \hat{y}_{it} - y_t, i = 1, 2$, the loss related to forecast i is given by $g(e_{it})$ which is a function of e_{it}. $g(e_{it})$ is a loss function that takes the value zero given no error, is never negative, and increases in size with the magnitude of the errors. The function is usually either the square $g(e_{it}) = e_{it}^2$, or the absolute value $g(e_{it}) = |e_{it}|$, of e_{it}.

The loss differential between the two forecasts is defined as

$$d_t = g(e_{1t}) - g(e_{2t})$$

and states that the two forecasts have equal accuracy if the loss differential is zero in expectation for all t. Here $i = 1$ is the structural model and $i = 2$ is the benchmark.

The null hypothesis to be tested is thus;

$$H_0 : E(d_t) = 0, \forall t$$

and the alternative hypothesis is

$$H_0 : E(d_t) \neq 0, \forall t$$

The null hypothesis is that the forecasts have same accuracy while the alternative hypothesis is that they differ in their accuracy.

If the forecasts are h –step–ahead, for $h \geq 1$ the Diebold–Mariano test statistic is given by

$$DM = \frac{\bar{d}}{\sqrt{\frac{\hat{\gamma}_d(0) + 2\sum_{k=1}^{h-1} \hat{\gamma}_d(k)}{T}}}$$

The null is rejected if the DM statistic is outside the interval $-z_{\frac{\alpha}{2}}$ to $z_{\frac{\alpha}{2}}$. If the statistic is negative it is in favor of the structural model, and a statistic below $-z_{\frac{\alpha}{2}}$ implies that the predictive ability of the structural model is significantly better at the α significance level compared to the benchmark.

A.4 *Clark and West Test*

The Clark and West (2006) is quite similar to the Diebold and Mariano test. It defines a loss function based on the square of the difference between forecasts and the actual values, $g(e_{it}) = (e_{it})^2$ where $e_{it} = y_t - \hat{y}_{it}$. Here $i = 1$ is the benchmark and $i = 2$ is the structural model. y_{it} are the forecasts obtained from two models, a benchmark model and a structural model, and y_t is the actual series. As opposed to the Diebold and Mariano test, the Clark and West test adds an adjustment term in the loss differential function d_t where

$$d_t - adj_t = g(e_{1t}) - (g(e_{2t}) - adj_t) = (y_t - \hat{y}_{1t})^2 - (y_t - \hat{y}_{2t})^2 + (\hat{y}_{1t} - \hat{y}_{2t})^2$$

This is to account for the a larger number of predictors in cases where the alternative and null models are nested. It tests the null hypothesis $H_0 : E(d_t) = 0, \forall t$ vs. the alternative hypothesis $H_1 : E(d_t) > 0$.

The Clark and West test statistic is given by

$$CW = \frac{\hat{d}}{(\widehat{avar}(\hat{d}))^{\frac{1}{2}}}$$

where $avar(d)$ is the variance of d_t.

Appendix B Tables

B.1 *Stationarity Tests*

Notes. The tables reports the test statistics and p–values of the ADF and KPSS test on levels and the first differences of the variables. s, p and vix are in logs. The null for ADF test is that the series contains a unit root. The null for KPSS test is that the series is stationary. The lag length is based on the Bayeian (Schwarz) information criterion with maximum 52 lags. The model is an AR model with drift an no time trend. ***, **, * denotes rejection at the 1%, 5% and 10% levels. The first sample is from 14.10.2005 to 03.01.2014. The last sample is from 10.01.2014 to 26.02.2021.

Table B.1.1: Testing for Stationarity – First sample

Variable	ADF				KPSS				I(d)
	Levels		First difference		Levels		First difference		
	Stat.	P–value	Stat.	P–value	Stat.	P–value	Stat.	P–value	
s	-2.092	0.252	-20.887***	0.000	5.394 ***	<0.01	0.0794	>0.1	I(1)
i^{diff}	-1.754	0.407	-15.559***	0.000	5.430***	<0.01	0.098	>0.1	I(1)
p	-1.810	0.379	-22.335***	0.000	9.848***	<0.01	0.056	>0.1	I(1)
vix	-2.742*	0.071	-25.318***	0.000	2.095***	<0.01	0.043	>0.1	I(1)
fin	-0.680	0.849	-9.470***	0.000	10.654***	<0.01	0.410*	0.0730	I(1)
$nonfin$	-1.400	0.585	-15.426***	0.000	1.323***	<0.01	0.232	>0.1	I(1)

Table B.1.2: Testing for Stationarity – Last sample

Variable	ADF				KPSS				I(d)
	Levels		First difference		Levels		First difference		
	Stat.	P–value	Stat.	P–value	Stat.	P–value	Stat.	P–value	
s	-1.715	0.4269	-19.575***	0.000	14.968***	<0.01	0.0184	>0.1	I(1)
i^{diff}	-2.401	0.147	-10.647***	0.000	0.308	>0.1	0.106	>0.1	I(1)
p	-2.478	0.126	-16.636***	0.000	9.848***	<0.01	0.162	>0.1	I(1)
vix	-4.793***	0.000	-22.521***	0.000	2.764***	<0.01	0.015	>0.1	I(1)
fin	0.940	0.996	-15.727***	0.000	12.413***	<0.01	0.304	>0.1	I(1)
$nonfin$	0.684	0.991	-16.72***	0.000	1.621***	<0.01	0.443*	0.059	I(1)

B.2 *Cointegration Tests*

Notes. The tables shows cointegration tests for the two subsamples. It tests for cointegration between Financial and Non–financial flows and the log EURNOK exchange rate, and for cointegration when including oil price, VIX, and interest differential in the system. Panel A reports the Johansen Trace statistics. It allows for a linear trend in the data. Panel B reports the test statistics and p–values of the ADF test on the residuals of the cointegrating regression with log spot exchange rate as the dependent variable. ***, **, * denotes rejection at the 1%, 5% and 10% levels respectively. The lag selection is based on the Bayesian (Schwarz) information criterion with an optimal lag length of two for all cases. The first sample is from 14.10.2005 to 03.01.2014. The last sample is from 10.01.2014 to 26.02.2021.

Table B.2.1: Testing for Cointegration – First sample

Exchange rate and cumulative order flow				
Panel A: Johansen cointegration test				
	Financial		Non–financial	
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	30.213***	0.002	7.931	0.830
$r = 1$	5.622	0.239	2.319	0.735
Panel B: Engle–Granger cointegration test				
ADF	-3.733*	0.060	-2.455	0.547
Exchange rate, cumulative order flow and macro variables				
Panel A: Johansen cointegration test				
	Financial		Non–financial	
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	138.198***	0.001	86.110***	0.009
$r = 1$	70.516***	0.001	36.361	0.659
$r = 2$	28.324	0.239	21.147	0.660
$r = 3$	16.144	0.168	11.631	0.521
$r = 4$	6.660	0.146	4.191	0.454
Panel B: Engle–Granger cointegration test				
ADF	-3.810**	0.038	-3.126	0.677

Table B.2.2: Testing for Cointegration – Last sample

Exchange rate and cumulative order flow

Panel A: Johansen cointegration test

	Financial		Non–financial	
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	32.879***	0.001	16.673	0.146
$r = 1$	8.820	0.058	2.094	0.769

Panel B: Engle-Granger cointegration test

ADF	-4.324	0.012	-3.885	0.041

Exchange rate, cumulative order flow and macro variables

Panel A: Johansen cointegration test

	Financial		Non–financial	
Null hypothesis	Stat.	P–value	Stat.	P–value
$r = 0$	163.012***	0.001	107.346	0.001
$r = 1$	97.857***	0.001	42.634	0.374
$r = 2$	53.456***	0.001	15.494	0.939
$r = 3$	22.647**	0.023	6.302	0.936
$r = 4$	7.206	0.117	2.250	0.746

Panel B: Engle–Granger cointegration test

ADF	-5.315***	0.011	-2.261	0.890

B.3 *ECM 10.01.2014–27.12.2019*

Table B.3.1: ECM – Last sample excl. Covid–19 pandemic

	1 week		4 weeks		12 weeks	
	(1)	(2)	(1)	(2)	(1)	(2)
α	0.002	0.001	0.006	0.005	0.014	0.011
	(2.877)***	(2.812)***	(2.789)***	(2.665)***	(2.353)**	(2.310)**
fin_t	0.004	0.003	0.010	0.007	0.012	0.009
	(7.062)***	(5.383)***	(7.135)***	(6.590)***	(3.189)***	(2.853)***
Δi_t^{diff}		-0.057		-0.014		-0.008
		(-3.380)***		(-0.501)		(-0.311)
Δp_t		-0.061		-0.060		-0.055
		(-5.352)***		(-3.515)***		(-2.702)***
Δvix_t		0.017		0.013		0.019
		(7.159)***		(4.038)***		(3.113)***
EC_{-n}	-0.087	-0.111	-0.246	-0.328	-0.719	-0.843
	(-3.768)***	(-4.787)***	(-2.791)***	(-3.001)***	(-3.857)***	(-3.988)***
Adj. R^2	0.213	0.432	0.407	0.555	0.522	0.678

Notes. The dependent variable is the one, four, and twelve week change in the log EURNOK exchange rate (log(NOK/EUR_t) - log(NOK/EUR_{t-n})), where n denotes the number of weeks the return is measured over. The sample spans from 10.01.2014 to 27.12.2019. Δs_t, Δp_t and Δvix_t represent the change of the natural logarithm of the variables EURNOK exchange rate, Brent Crude Oil price denominated in U.S. dollars and the CBOE Volatility index for $t-n$ to t. Δi_t^{diff} is the change in the interest rate differential between Norway and the EU. Financial order flow is the change in net positions of the financial customers and is measured in EUR 100 million. The order flow coefficient measures the impact of a one–standard deviation change in the flow. EC_{-n} is the error correction term from the cointegration analysis, lagged witn n periods. Standard errors are robust, measured with Newey–West HAC procedure. Statistical significance at the 1, 5 and 10 percent level is denoted by "***", "**" and "*" respectively.

B.4 *Clark and West Test*

Table B.4.1: Clark and West's (2006) Test Statistics

	A. Hybrid Model		B. Micro Model	
Window Size:	Stat.	P–value	Stat	P–value
1/2	5.070***	0.000	3.238***	0.001
1/3	6.753***	0.000	3.762***	0.000
1/4	7.967***	0.000	4.813***	0.000
1/5	7.716***	0.000	4.965***	0.000
1/6	7.879***	0.000	5.053***	0.000
1/7	7.991***	0.000	5.282***	0.000
1/8	7.736***	0.000	4.992***	0.000
1/9	7.596***	0.000	5.230***	0.000
1/10	7.756***	0.000	5.451***	0.000

Notes. The table reports Clark and West's (2006) statistics and p–values. The null hypothesis is equal predictive accuracy as a random walk without drift. Significant statistics implies that the model being tested outperforms the benchmark. ***, **, * denotes rejection at the 1%, 5% and 10% levels. Panel A reports the p–values for the Hybrid model, eq. (2), and panel B reports results for the Micro model, eq. (1). The window size is reported in the first column as a fraction of the full sample size.

REFERENCES

Akram, Q. F. (2000a). *PPP Despite Real Shocks: An Empirical Analysis of The Norwegian Real Exchange Rate* (Norges Bank Working Paper No. 7). http://hdl.handle.net/11250/2500404

Akram, Q. F. (2000b). *When does the oil price affect the Norwegian exchange rate?* (Norges Bank Working Paper No. 8). http://hdl.handle.net/11250/2500400

Akram, Q. F. (2004). Oil prices and exchange rates: Norwegian evidence. *The Econometrics Journal*, *7*(2), 476–504. https://doi.org/10.1111/j.1368-423X.2004.00140.x

Akram, Q. F. (2020). Oil price drivers, geopolitical uncertainty and oil exporters' currencies. *Energy Economics, 89*, 104–801. https://doi.org/10.1016/j.eneco.2020.104801

Bank for International Settlements. (2019). *Triennial Central Bank Survey of Global foreign exchange market turnover in 2019*. BIS. https://www.bis.org/statistics/rpfx19fxannex.pdf

Bergo, J. (2003, March 27). *Inflation targeting with a fluctuating exchange rate*. Norges Banj. https://www.norges-bank.no/aktuelt/nyheter-og-hendelser/Foredrag-og-taler/2003/2003-03-27-2/

Bernhardsen, T., Kloster, A., & Syrstad, O. (2012). *Risk premiums in NIBOR and other countries' interbank lending rates* (Norges Bank Working Paper No. 21). http://hdl.handle.net/11250/2507182

Bernhardsen, T., & Røisland, O. (2000). Factors that influence the krone exchange rate. *Norges Bank. Economic Bulletin*, *71*(4), 143–151. https://norges-bank.brage.unit.no/norges-bank-xmlui/handle/11250/2505003

Bjønnes, G. H., Rime, D., & Solheim, H. O. A. (2005). Liquidity provision in the overnight foreign exchange market. *Journal of International Money*

and Finance, *24*(2), 175–196.
https://doi.org/10.1016/j.jimonfin.2004.12.003

Brooks, C. (2014). *Introductory econometrics for finance* (3rd ed.). Cambridge University Press.

Chen, Y., & Rogoff, K. (2003). Commodity currencies. Journal of *International Economics*, *60*(1), 133–160.
https://doi.org/10.1016/S0022-1996(02)00072-7

Cheung, Y. W., Chinn, M. D., & Pascual, A. G. (2005). Empirical exchange rate models of the nineties: Are any fit to survive? *Journal of International Money and Finance*, *24*(7), 1150–1175.
https://doi.org/10.1016/j.jimonfin.2005.08.002

Chinn, M. D., & Moore, M. J. (2011). Order Flow and the Monetary Model of Exchange Rates: Evidence from a Novel Data Set. *Journal of Money, Credit and Banking*, *43*(8), 1599–1624.
https://doi.org/10.1111/j.1538-4616.2011.00460.x

Clark, T. E., & West, K. D. (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics*, *135*(1), 155–186.
https://doi.org/10.1016/j.jeconom.2005.07.014

Diebold, F., & Mariano, R. (1995). Comparing Predictive Accuracy. *Journal of Business & Economic Statistics*, *13*(3), 253–263.

Dimand, R. W. (1999). Irving Fisher and the Fisher Relation: Setting the Record Straight. *The Canadian Journal of Economics*, *32*(3), 744–750.
https://doi.org/10.2307/136447

Engle, R. F., & Granger, C. X. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, *55*(2), 251-276.https://doi.org/10.2307/1913236

Evans, M. D. D. (2009). Order flows and the exchange rate disconnect puzzle. *Journal of International Economics*, *80*(1), 58-71. 10.1016/j.jinteco.2009.05.001

Evans, M. D. D., & Lyons, R. K. (1999). *Order Flow and Exchange Rate Dynamics.* (National Bureau of Economic Research Working paper No. 7317). 10.3386/w7317

Evans, M. D. D., & Lyons, R. K. (2002). Order Flow and Exchange Rate Dynamics. *Journal of Political Economy*, *110*(1), 170-180. https://doi.org/10.1086/324391

Evans, M. D. D., & Lyons, R. K. (2005). Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting. *American Economic Review*, *95*(2), 405–414. http://dx.doi.org/10.2139/ssrn.646123

Evans, M. D. D., & Lyons, R. K. (2006). Understanding order flow. *International Journal of Finance & Economics*, *11*(1), 3-23. https://doi.org/10.1002/ijfe.287

Evans, M. D. D., & Lyons, R. K. (2012). Exchange Rate Fundamentals and Order Flow. *The Quarterly Journal of Finance*, *2*(4), 1–63. https://doi.org/10.1142/S2010139212500188

Evans, M. D. D., & Rime, D. (2016). Order flow information and spot rate dynamics. *Journal of International Money and Finance*, *69*, 45–68. https://doi.org/10.1016/j.jimonfin.2016.06.018

Ferraro, D., Rogoff, K., & Rossi, B. (2015). Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance*, *54*, 116–141. https://doi.org/10.1016/j.jimonfin.2015.03.001

Flatner, A. (2009). Norwegian krone no safe haven. *Department for Market Operations and Analysis, Norges Bank, 3.* http://hdl.handle.net/11250/2558959

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3

King, M. R., Osler, C. L., & Rime, D. (2011). *Foreign Exchange Market Structure, Players and Evolution.* (Norges Bank Working Paper No. 10). http://dx.doi.org/10.2139/ssrn.1935858

Kleivset, C. (2012). *Fra fast valutakurs til inflasjonsmaal* (Norges Bank Working Paper No. 30). http://hdl.handle.net/11250/2507170

Kohlscheen, E., Fernando, A., H., & Schrimpf, A. (2016). *When the Walk is Not Random: Commodity Prices and Exchange Rates* (Bank of International Settlements Working Paper No. 551). https://ssrn.com/abstract=2752433

Leonard, G., Moran, N., M., & Samuel, L. (2020). Battle of the Benchmarks: Brent Crude Oil and West Texas Intermediate. *Cornerstone Research.* https://www.cornerstone.com/Publications/Articles/Battle-of-the-Benchmarks-Brent-Crude-Oil-and-West-Texas-Intermediate/Battle-of-the-Benchmarks.pdf

Lyons, R. K. (2001). *The Microstructure Approach to Exchange Rates* (1st ed.). The MIT Press.

Lyons, R. K. (2003). Explaining and Forecasting Exchange Rates with Order Flows. *Prepared for the Third Economic Policy Forum*, *96*(4), 107–127. https://doi.org/10.3917/ecoi.096.0107

Macdonald, R., & Taylor, M. P. (1993). The Monetary Approach to the Exchange Rate: Rational Expectations, Long-Run Equilibrium, and Forecasting. *Staff Papers (International Monetary Fund)*, *40*(1), 89–107. https://doi.org/10.2307/3867378

Marsh, I., W., & O'Rourke, C. (2005). Customer Order Flow and Exchange Rate Movements: Is There Really Information Content? *Cass Business School Research Paper.* http://dx.doi.org/10.2139/ssrn.704944

Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics*, *14*(1), 3–24. https://doi.org/10.1016/0022-1996(83)90017-X

Meese, R., & Rogoff, K. (1988). Was It Real? The Exchange Rate-Interest Differential Relation over the Modern Floating-Rate Period. *The Journal of Finance*, *43*(4), 933–948. https://doi.org/10.1111/j.1540-6261.1988.tb02613.x

Meyer, E., & Skjelvik, J. (2006). Statistics on Foreign Exchange Transactions – New Insight into Foreign Exchange Markets. *Norges Bank. Economic Bulletin*. https://norges-bank.brage.unit.no/norges-bank-xmlui/handle/11250/2504301

NOU 2020:8. (2020). *Grunnlaget for inntektsoppgjoerene 2020*. Arbeids– og sosialdepartementet. https://www.regjeringen.no/no/dokumenter/nou-2020-8/id2714942/

Obstfeld, M., & Rogoff, K. (2001). *The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?* (National Bureau of Economic Research Working Paper No. w7777). https://ssrn.com/abstract=235703

Olje– og energidepartementet. (2020). *Exports of Oil and Gas*. Norsk Petroleum. https://www.norskpetroleum.no/en/production-and-exports/exports-of-oil-%20and-gas/

Rime, D., & Sojli, E. (2006). Order flow analysis of exchange rates. *Norges Bank. Economic Bulletin*. http://hdl.handle.net/11250/2504296

Rogoff, K. (1996). The Purchasing Power Parity Puzzle. Journal of *Economic Literature*, *34*(2), 647–668.

Rossi, B. (2013). Exchange Rate Predictability. *Journal of Economic Literature*, *51*(4), 1063–1119. https://doi.org/10.1257/jel.51.4.1063

Saskia, E. (2016). *Nonlinearities in the Relationship Between Oil Price Changes and Movements in the Norwegian Krone* (Norges Bank Working Paper No. 18). http://hdl.handle.net/11250/2506529