BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

The relation between oil price and exchange rate: Evidence from Norway

Navn: Even Opsal, Mona Therese Rye

Start: 02.03.2017 09.00

Finish: 01.09.2017 12.00

The relation between oil price and exchange rate: Evidence from Norway

September 1st 2017

Authors: Mona Therese Rye
Even Opsal

Supervisor: Hamid Boustanifar

Master of Science in Business with major in Finance

Table of Content

Abstract

This paper investigates if changes in the Crude Brent oil price can predict changes in the nominal Norwegian Krone – U.S. Dollar exchange rate using daily, weekly, monthly, and quarterly datasets. The predictability content is evaluated through several exercises using one-step-ahead pseudo out-of-sample forecasts. The test results yield a robust out-of-sample relationship using contemporaneous oil price changes at all test frequencies. We also find that lagged oil prices can predict future exchange rates using daily and weekly frequencies.

Our main contribution is the evidence that oil prices can significantly forecast future exchange rates consistently for the sample period under consideration and that using the correct benchmark for oil price is crucial for capturing predictability. In addition, we include more recent data and we consider a new frequency where a transitory predictive ability is found using weekly data.

Acknowledgements

We would like to express gratitude towards our supervisor Hamid Boustanifar for valuable guidance and continuous support during the work with our Master Thesis.

1.0 Introduction

This paper study the relationship between changes in Crude Brent oil prices and changes in the nominal Norwegian Krone – U.S. Dollar (NOK/USD) exchange rate using daily, weekly, monthly and quarterly frequencies.

It is well known that activities from oil and natural gas have contributed significantly to Norway's economic growth over the past 40 years, with the sector constituting 42 % of the country's export since 1971 (Oljedirektoratet, 2017). In recent years, the oil price has dramatically increased in volatility and we have seen a downward shift in the commodity price. Simultaneously, we have seen a depreciation of the Norwegian Krone against major currencies such as the U.S. Dollar and the Euro. Øystein Olsen, CEO of the Norwegian Central Bank, informed the public during their yearly hearing in the Standing Committee on Finance and Economic Affairs, on the 15th of May 2017 that he believes developments in the oil market will continue to be the most central driver for the Norwegian Krone in the years to come.

Øystein Olsen's statement is coherent with well-established theories on the field, suggesting that countries exporting oil in large quantities have a currency depending on shifts in the price of oil (Bjørk, Mork & Uppstad, 1998; Akram, 2004; Chen, Rogoff & Rossi, 2010; Ferraro, Rogoff & Rossi, 2015). In particular, we expect the currency to strengthen when the oil price increases, and to weaken when the oil price decreases. Figure 1 shows how the Crude Brent price and the U.S. Dollar – Norwegian Krone (USD/NOK) exchange rate evolves over time and

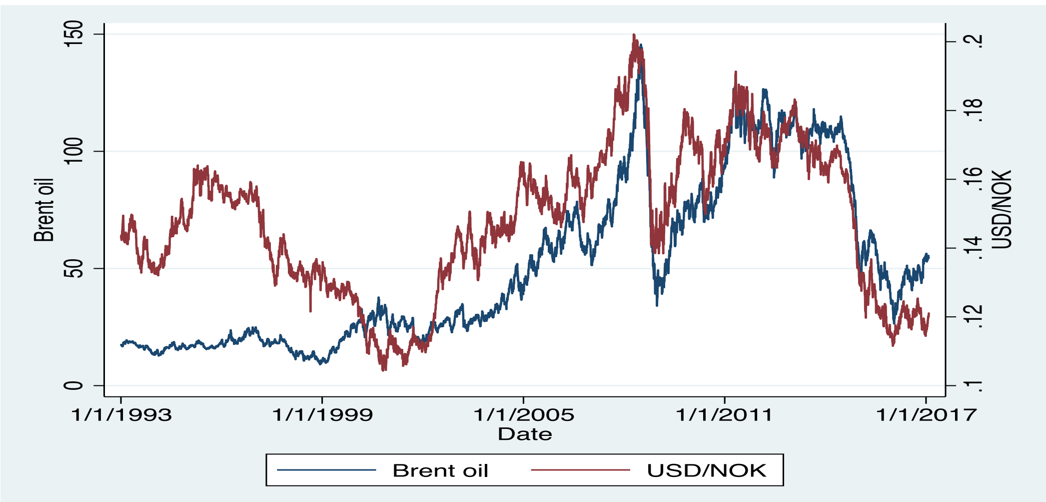


Figure 1. *Time series of Brent oil spot price and USD/NOK exchange rate.*

suggests a high correlation occurring from around year 2003. This inverse relationship of the exchange rate is used in the graph for better illustration of the correlation. It seems clear that an increase in the Crude Brent price is followed by an appreciation of the Norwegian currency. However, researchers have found it difficult to predict future exchange rates using commodity prices. Most studies on exchange rate movements conclude the random walk to be the superior forecaster above any estimated model (Meese & Rogoff, 1983a; Diebold & Nason, 1990; Frankel & Rose, 1995; Cheung, Lai & Bergman, 2004; Engel & West, 2005). Additionally, very few studies have researched the Norwegian currency in particular.

In their study, Chen et al. (2010) found evidence that exchange rates significantly predicts future commodity prices. Although, when they analyzed the reveresed relationship that we are considering, they could never consistently forecast exchange rate movements above a random walk. Ferraro et al. (2015) did find an out-of-sample relationship between the West Texas Intermediate (WTI) crude oil and the NOK/USD exchange rate, but only when considering contemporaneus oil prices at daily and monthly frequencies. When they analyzed the true out-of-sample forecasting model using lagged crude oil prices, the predictability broke down. Signifcance was to be found only at shorter periods during their sample using daily frequency.

Our study found significant predictability in the pseudo out-of-sample model using contemporaneus oil price changes for both daily, weekly, monthly, and quarterly frequencies. Furthermore, we were able to consistently and significantly predict the future NOK/USD exchange rate above the random walk using lagged oil price changes with daily data. Ferraro et al. (2015) conclude that short-horizon predictability has never been convincingly demonstrated in the literature, especially with their high statistical significance levels. With this in mind, and after researching the field, we conclude with a new finding that commodity prices can consistently and significantly predict exchange rates. We were also able to find this link with weekly frequency when allowing for time variability in the performance of the model. With several papers showing that the Diebold and Mariano (1995) test statistic is undersized (Rogoff &Stavrakeva, 2008; Ferraro et al., 2015) we conclude that our significant results are robust when compared to other test statistics. Further analyses reveal that Crude Brent is the correct type of oil to use in a Norwegian context, and is in fact the reason why we are able to significantly predict the future exchange rate above existing literature.

In addition, our study find that most of the extreme values is in the period categorized as the financial crisis. According to Brooks (2014, 214) it is justified to remove observations related to extreme events that are unlikely to be repeated. We therefore perform a forecasting exercise without 15 of these observations, which further improves the forecasting ability. Our forecasting model with interest rate differentials concurs with previous findings that they have little predictability content for exchange rates.

In our study, we apply the first difference of the logarithm to exchange rates and oil prices. All forecasts are compared to those of a random walk using Diebold and Mariano`s (1995) test statistic. Our main focus is on the two forecasting models employed by Ferraro et al. (2015). The first model is an out-of-sample fit model where we use contemporaneous oil prices and the second model is a truly out-of-sample forecast using lagged oil prices. Rolling regressions is applied for both models to estimate the parameters.

We first analyze the in-sample fit of both contemporaneous oil prices and lagged oil prices using simple Ordinary Least Squares (OLS) regressions. The contemporaneous oil price is statistically significant at any standard level, and for all frequencies. The lagged oil price is only significant using daily and quarterly data. Analyzing the predictability through one-step-ahead pseudo out-of-sample forecasting, we find that contemporaneous realized oil prices do predict the nominal NOK/USD exchange rate at all frequencies. Our results are robust at daily, weekly, and monthly levels. At quarterly frequency, the empirical evidence is favoring our model, as well. Although, this is only significant using the largest in-sample window size at the 5% level.

We also find evidence that lagged oil prices are consistent and significant predictors of the NOK/USD exchange rates at daily frequencies. This result is however less robust and only significant when using half of the total sample as in-sample window size.

Further, we employ the fluctuation test by Giacomini and Rossi (2010) to obtain insight on whether the forecasting performance of our model varies over time. This is relevant, as several researchers have found evidence of parameter instabilities in econometric models. The test calculates rolling averages of the out-of-sample difference in Mean Squared Forecasting Errors (MSFE) over a preset window over the entire sample. We find several periods where our true forecasting model with lagged oil prices outperforms the random walk in weekly frequency. In monthly and quarterly frequencies, our model never forecast better than the random walk.

Although, our main focus is on the two forecasting models from Ferraro et al. (2015), we use these models in several tests to further investigate the relationship. Since we were able to find additional predictability compared to results from Ferraro et al. (2015) we find it interesting to investigate the source of this additional predictability. Our data differs with longer time horizon and different benchmark for crude oil. We therefore replicate the previous forecasting with lagged oil price changes in two different exercises. First with the same sample length as Ferraro et al. (2015) and secondly with Crude WTI as benchmark for oil prices. In conclusion, we see that it is only when we use Crude Brent as benchmark for oil that we can predict the exchange rate, and to our surprise, the extended sample size from 2010 until 2017 yields more uncertainty in our forecasts. This is coherent with Crude Brent being produced in the North Sea and is therefore considered the most influential benchmark for crude oil in Europe. Although the two oil price indices have moved in tandem before year 2010, we impose the evidence found by Chen, Huang and Yi (2015) of a structural break in this year which has lead to a persistent WTI – Brent spread as a possible explanation.

Further investigation of our data set reveals that 15 out of the 30 most extreme values in our whole sample at daily data are during the financial crisis. Given that there is such a significant number of extreme values corresponding to a specific historical event we find it relevant to conduct a test where these 15 values are removed from the total 6283 observations. We find that the financial crisis did have a disruptive impact on the exchange rates for a short period, and that accounting for it will give more accurate prediction. This crisis was such a rare phenomenon, that we assume it will not occur in a foreseeable future.

Further, we apply interest rate differentials to analyze if changes in interest rates between Norway and the U.S. could be an explanatory factor for the fluctuations of the Norwegian Krone. We do not find any strong significant evidence to support this claim when comparing it against the effect Crude Brent has on the Norwegian Krone. To verify our results, and assure that there is no dollar-effect disrupting our data, we performed a robustness test using the Great British Pound, verifying that our results are not plagued by the dollar-effect.

Our paper contributes to existing literature by a more concentrated focus on the Norwegian Krone and the Crude Brent oil. More importantly, our study provides new and interesting evidence in the field of exchange rate movements. In particular, we contribute with evidence that oil prices can consistently and significantly predict future exchange rates. Even without taking instabilities into account. Furthermore, our results show that the choice of benchmark for oil price is important when investigating the relationship between oil prices and exchange rates. Not only has this never been found in previous literature, it is also an important stepping-stone for further research. In addition, we introduce a new dataset with weekly frequency as suggested by Ferraro et al. (2015). Also here we find that Crude Brent oil prices significantly predict the Norwegian Krone – U.S. Dollar exchange rate. Finally, our study adds more recent data, which gives us a longer time horizon from when the time the Norwegian Krone became a floating currency.

The paper is organized in the following sections; we present previous literature and theories that are relevant for our paper, in section 2. Our research question and hypotheses is in detail presented in section 3. Presented in section 4, is the data that is used in our empirical research, and our reasoning for our choices. In section 5, we present introductory statistics, the logarithmic change applied for our variables, and a brief explanation of Diebold and Mariano`s test statistic which is used throughout our paper. Section 6 covers our main forecasting models and results. In section 7 and 8, we present our results from analyzing time variation in performance of our forecasting, and the source of additional predictability, respectively. Section 9 investigates the impact of the financial crisis while section 10 study the predicatbility of interest rate differentials. This is followed by a robustness check for the dollar effect in section 11 and our limitations in section 12. Finally, in section 13 we provide an overall conclusion of our findings.

2.0 Theoretical framework

In the following section, we will present previous literature that is relevant for our paper. Theories on exchange rate movements will also be applied to increase the significance and accuracy of our results.

2.1 Literature review

Since the modern floating exchange rate era, reserachers have found it difficult to predict exchange rate movements. Meese and Rogoff (1983a) found early that any estimated exchange rate model could never forecast better than the random walk. This is consistent with similar work on the area (Diebold & Nason, 1990; Frankel & Rose, 1995; Cheung et al., 2004).

Mark (1995) found some evidence of predicatbility content for log exchange rate changes in long-horizons of up to four years. In horizons from one quarter and shorter there were no evidence found. Also, Cheung, Chinn and Pascual (2005) and Engel and West (2005) concluded that no fundamentals outperform the random walk, except for long time periods. Engel and West (2005) argued that as the discount factor is near unity, with one or more of the driving variables following a near unit root process; the exchange rate will appear to be close to a random walk when the period is short. Although at a longer time period this might be less applicable. With this in mind, the long-horizon results have both been criticized and confirmed while the absence of evidence in short-horizons still stands (Ince, Molodtsova & Papell, 2016).

According to Rogoff and Stavrakeva (2008) there have been a few influential papers reporting a somewhat more positive short-term forecasting result (Gourinchas & Rey, 2007; Engel, Mark & West, 2007). They do however conclude that most of the popular exchange rate models from existing literature are plagued by several sources of overly optimism, such as failing to produce robust forecasts over different sample periods. In particular, their models only outperform the random walk in one period of their sample, giving no warranty to believe that the relationship will be preserved in the future.

Chen et al. (2010) analyzed the out-of-sample relationship between the main commodity currencies, fundamentals, and commodity prices. Although they found that exchange rates have quite robust power in predicting global commodity prices the reversed relationship did not hold. Instead they report that their commodity currencies exhibit the same Meese and Rogoff puzzle as other major currencies in the literature; none of the fundamentals, including commodity prices, consistently forecast exchange rate movements better than the random walk.

The models applied in this study is from the paper by Ferraro et al. (2015). They investigate the predictablity of the Canadian – U.S. Dollar exchange rate, and the Norwegian Krone – U.S. Dollar exchange rate using spot prices of Crude West Texas Intermediate (WTI) oil. The predictability is considered through an out-of-sample fit regression using contemporaneus oil prices and a truly out-of-sample forecasting model using lagged oil prices. For the NOK/USD exchange rate their results suggest a short-term relationship when considering the contemporaneus model for daily and monthly frequencies. For the truly out-of-sample forecasting model, daily lagged commodity prices can only be statistically significant predictors of the exchange rate when allowing for time variation in the relative perfomance of the model. They were not able to obtain significant results at frequencies that were monthly or quarterly. In both their out-of-sample, and in-sample analysies, they state that the frequency have an impact of the predictability of the data. Additionally, they cannot find that non-linearity and cointegration models perform better than the simple linear model.

Akram (2004) studied the Norwegian Krone in particular and found a non-linear negative relationship between the Norwegian exchange rate, and the oil prices only when the oil price was below USD 14 and falling. Also related to the Norwegian context is the paper by Yousefi and Wirjanto (2004). They investigated the impact of interference by OPEC as a price maker on the crude oil market, when the USD exchange rate fluctuates. Their findings show a negative correlation, and conclude that the OPEC members are not able to unify their prices to control the market. Hence, complying with the assumption from market analysts today, that OPEC is not a price maker.

In their paper, Faust, Rogers and Wright (2003) found that real-time data performs consistently better than revised data for a fixed time period. Their research is focused only on simple but important models within the literature of exchange rate forecasting.

2.2 Random Walk

The theory of a random walk states that one cannot use past actions to predict future outcomes of an asset, implying that past trends or changes are independent from the assets future movements. Therefore, a random walk forecast for changes in the exchange rate will be zero change. Malkiel (2017) argue in his book “A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing”, that index funds on the Standard & Poor's 500-Stock Index have significantly outperformed average actively managed funds since 1969. Highlighting that asset prices typically exhibit a random walk.

According to existing literature the random walk has superior forecasting ability for exchange rates, compared to various structural and time series models (Meese & Rogoff, 1983a,b; Mark, 1995; Chinn & Meese, 1995; Rossi, 2013; Ferraro et al., 2015). Furthermore, Kilian (1999) argues that between the two versions of the random walk, the random walk without drift will demand more accuracy from the competing model in order to conclude a significantly better forecast. We therefore apply this version in order to have more robust results for our forecasting models.

2.3 Interest Rate Differentials

The yield on government bonds is priced from the degree of risk it carries. Hence, there is a difference in the quoted price on government bonds issued from different countries. To account for this variation, we apply Interest Rate Differentials. This theory can be applied as a gap measure on all interest-bearing assets that are comparable. The theory subtracts the foreign rate from the domestic rate, or vice versa depending on the application of the variable. As an effect of this gap, the country with the highest interest rate yielded will see an increase in demand for its currency, which can lead to an appreciation. Although, there is no strong relationship between real exchange rates and real interest rate differentials in either short- or long-term according to the findings of Meese and Rogoff (1988) there have been observations of this occurring as the financial crisis unveiled in August of 2007. As an effect of Norway`s higher rates than its European counterpart the demand for the Norwegian Krone and Norwegian deposits increased, leading to an appreciation for a short period against the Euro and the U.S. Dollar.

2.4 Purchasing power parity

The theory of purchasing power parity is based on the law of one price, and states that; identical goods should have the same price in every country, after the exchange rates are adjusted. One such popular purchasing power parity index is the Big Mac Index. The Economist has investigated the price of McDonald’s popular hamburger since 1986, and the over-/undervalue from country to country. As the theory assumes that offset prices are changing due to inflation, it therefore eliminates any opportunity for arbitrage. Rogoff (1996) found it extremely hard to use purchasing power parity to explain high volatility fluctuations in the exchange market in a short period. Applying it to long periods have a consensus on suggesting that the speed of convergence is extremely slow, and should give results.

2.5 Terms-of-Trade

As a variable representing the value of a country's exports relative to its imports, terms-of-trade is significantly relevant to strengthen the explanatory power of our study. If the terms-of-trade ratio appreciates above 1, it is a sign of improvement. That is, when a country's currency depreciates the export prices become relatively lower to foreign importers and vice versa for domestic importers. Accordingly, a depreciation of a country's currency will prompt export of goods. In Norway, the relatively strong Norwegian Krone until the oil price depreciation shock of 2014, inhibited export of other goods. That is, creating a shift in terms-of-trade for Norway due to the oil price shock.

Since changes in terms-of-trade usually come with fluctuations in exchange rates, it is mostly relevant for countries with a floating exchange rate. Hence, terms-of-trade should by theory be relevant for the Norwegian Krone, also if the size of the economy is taken into account.

3.0 Research question and hypotheses

Since 2014 the supply of crude oil, both Crude Brent and Crude WTI has risen to a higher level than the demand for crude oil. After having a stable increase for almost a decade, the change in the supply and demand curve in 2014 sent the price of crude oil from USD 115 in the summer of 2015, to below USD 30 in early 2016. The sudden change from a commodity with low volatility, to a highly volatile one, made way for major changes in the global economy just a few years after the financial crisis. Focusing on the macroeconomic impact this had on Norway, the consequences very many due to the high oil percentage of total export. Norway's largest company on the Oslo Stock Exchange, and the biggest oil company in Norway, Statoil ASA saw its share value go from NOK 194,80 in 2014, to NOK 97,90 at the lowest in 2016 (Oslo Børs). The country's banks took heavy losses in the offshore and connecting industries, mainland GDP staggered, unemployment increased and the Norwegian Krone depreciated. These events increased our interest on how the commodities affect currencies, and therefore we have been focusing on our research question: *Is there a significant connection between commodity prices and exchange rates?* We have chosen to focus on the relationship between the Norwegian Krone and Crude Brent. Usually the currency has been excluded from other papers due to the short valid sample size. Our main hypothesis is constructed to reflect the findings of former research.

H_0: There is no significant evidence that oil prices can forecast exchange rates.

(1)

H_A: There is significant evidence that oil prices can forecast exchange rates.

Since our data sample covers the period of the financial crisis, we will also address the following sub-hypothesis:

H_0: The financial crisis did not impact exchange rate predictability.

(2)

H_A: The financial crisis did have an impact on exchange rate predictability.

Finally, we test whether interest rate differentials can predict the exchange rate.

H_0: There is no significant evidence that interest rates can forecast the exchange rate.

(3)

H_A: There is significant evidence that interest rates can forecast the exchange rate.

4.0 Data

In our study, we focus exclusively on Norway. Our reasoning is that most major studies on the correlation between crude oil and exchange rate tend to discard the Norwegian Krone from its studies. Thus, we want to contribute to a better understanding on the potential impact the oil price has on the Norwegian Krone. Previous studies used the Crude WTI as their preferred type of oil. Hence, we will apply the Crude Brent, which is the oil exported from Norway.

As a proxy for Crude Brent spot, we have chosen to use the Brent-Forties-Oseberg-Ekofisk index (BFOE). Although it does not differ that much from the generic index on Crude Brent, the BFOE index gives the closest relation to Norway. Hence, we get a specific European index to work with. The BFOE and WTI indices are both retrieved from Bloomberg, and contain last trading price of the day. By applying this proxy instead of the mean price of the day, we have observations where it is harder to find predictive ability (Ferraro et al., 2015). As commodities have fewer trading days than currencies within a year, the dispersion in observed prices of the two time series contains potentially omitted explanatory observations. This was solved by a command in Bloomberg that adds the price the trading day before on a non-trading day, if other variables have observations on the given day.

The nominal NOK/USD exchange rate and the nominal Norwegian Krone - Great British Pound (NOK/GBP) exchange rate are also from Bloomberg, and contains the last price on the given trading day. On all variables, we have obtained daily, weekly, monthly and quarterly datasheets, still applying last trading price. Bloomberg retrieves the data in the following; the weekly data obtains the observation on every Friday, in the monthly set the observations are from the last trading day of the month, and in the quarterly data the observation is from the last trading day in the given quarter. Our data ranges from 01.01.1993-31.01.2017. Hence, we start after the Norwegian Krone became a free-floating currency. This gives us on the daily dataset a number of 6283 observations, the weekly dataset contains 1252, the monthly dataset contains 282, and finally the quarterly dataset contains 96 observations per variable.

For interest rates, we apply one year to maturity government bonds, all bonds are originally yields a one year rate, and the rates are nominal. To account for the different datasheets, we convert the interest rate from yearly to daily, weekly, monthly and quarterly. This is executed by dividing the yearly rate on 365 for daily, 52 for weekly, 12 for monthly and 4 for quarterly. Our data for the bonds is retrieved from Bloomberg and includes the following; U.S. Treasury Bill 1 year, and Norwegian Government Bonds 1 year.

5.0 Introductory statistics, the logarithmic change, and Diebold and Mariano`s test statistic

5.1 Introductory statistics

Figure 2 illustrates how the USD/NOK exchange rate and the Crude Brent oil price have evolved during our sample using daily data. The Crude Brent oil price is reported on the left y-axis and the USD/NOK on the right y-axis. Since the exchange rate is U.S. Dollar per unit of Norwegian Krone a low value means a weakening of the Norwegian Krone against the U.S. Dollar. The figure clearly indicates a high correlation from year 2003 and onwards. We can see that the drop in the Crude Brent oil price that has occurred in the later years is accompanied with a similarly drop in the Norwegian Krone. This connection between the two series is further confirmed with a strong positive correlation between the Crude Brent oil price and the USD/NOK exchange rate of 0,7231 in our daily sample.

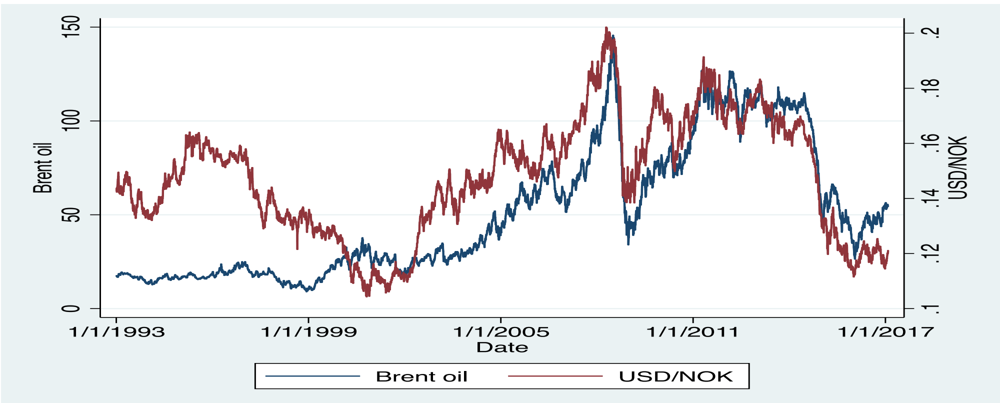


Fig 2: *The USD/NOK exchange rate and the Crude Brent oil.*

5.2 Logarithmic change

Throughout this paper we use the first difference of the logarithm on both exchange rates and oil prices. This means that we are interested in the change of the series instead of the spot rates at any given date. In addition to making our analysis comparable with those of Ferraro et al. (2015), this transformation has several useful properties. First, it mitigates heteroscedasticity through rescaling of the data. Secondly, we get a distribution that more closely resembles a normal distribution (Brooks, 2014).

The following formula is used, $\ln\left(\frac{x}{x_{-1}}\right) * 100$. Figure 3, shows how this transformation impact the residuals before and after the transformation. The residuals are collected from a simple Ordinary Least Squares (OLS) regression. The first histogram shows the distribution of the residuals collected from a regression with spot NOK/USD exchange rate as the dependent variable and the spot price of Crude Brent oil as the independent variable. The second histogram shows the residuals distribution from the same regression after the first difference of the logarithm is applied to the variables.

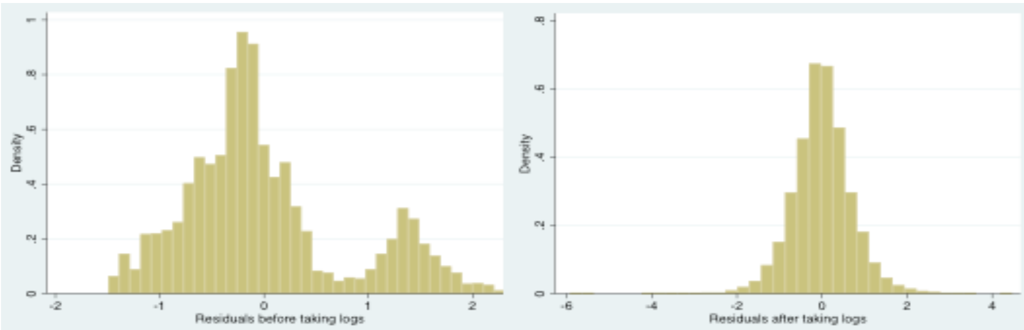


Fig 3: *Residuals before and after log change, daily data*

5.3 Diebold and Mariano test

In all our forecast models, we employ the Diebold and Mariano (1995) test as Ferraro et al. (2015). The test compares predictive accuracy between our forecast and the random walk by calculating the difference between our model`s MSFE and those of the random walk. The null hypothesis is of equal predictability between the two competing predictions is rejected at the 10%, 5%, and 1% significance level if $|\text{DM}|$ > 1,645, 1,96, and 2,33 respectively. When the test statistic is below -1,645 our model significantly outperforms the random walk.

Rogoff and Stavrakeva (2008) cite several papers concluding that the test statistic is undersized, meaning that it may not detect statistical significance even if it exists. Ferraro et al. (2015) support this claim by finding even stronger results in favor of their forecasting model using the alternative test statistic by Clark and West (2006). Therefore, should we find predictive content, these results would be very robust when compared to other test statistics. In addition, the test allows for forecast errors that are potentially non-Gaussian, nonzero mean, serially correlated, and contemporaneous correlated (Diebold & Mariano, 1995). By using a rolling window when estimating our parameters, we ensure that the test remains asymptotically valid even for nested models (Giacomini & White, 2006).

6.0 Can commodity prices forecast exchange rates?

In this section, we analyze the predictive relationship between Crude Brent oil prices and the nominal NOK/USD exchange rate by applying both in-sample fit and out-of-sample forecast. We follow Ferraro et al. (2015) in the out-of-sample procedure, which is divided in two parts. One with a contemporaneous model to measure the out-of-sample fit, and a second part with a truly out-of-sample forecast model using lagged changes in the Crude Brent oil price. Our research extends their study by adding more recent data and introducing the weekly frequency. In addition, we use Crude Brent instead of Crude WTI as benchmark for oil price since it is a more country specific proxy for Norway.

We find that Crude Brent oil prices are significant predictors for both contemporaneous and future NOK/USD exchange rates and that our results are consistent and robust for the sample period under consideration. We therefore based on findings in this section, reject the null of hypothesis 1 and conclude that there is significant evidence that oil prices can forecast exchange rates.

6.1 In-sample fit

We apply basic regressions to study the in-sample fit of our main models. The models we use are

$$\Delta ex_t = \alpha + \beta \Delta p_t + u_t, \quad t = 1, \ldots, T \tag{1}$$

$$\Delta ex_t = \alpha + \beta \Delta p_{t-1} + u_t, \quad t = 1, \ldots, T \tag{2}$$

where Δex and Δp denotes the first difference of the logarithm of respectively the NOK/USD exchange rate and the Crude Brent oil price. Section 5.2 shows our calculation of the first difference of the logarithm. Model (1) use the contemporaneous change in oil price as explanatory variable while model (2) use the lagged change. Parameters are estimated with simple OLS regressions using the entire dataset with daily, weekly, monthly, and quarterly frequencies.

6.1.1 Empirical results

The results reported in table 1 shows that in model (1) the coefficient estimates for the growth rate of oil are negative and highly significant at all frequencies. Suggesting that in daily frequency an oil price increase of 1 percent would lead to a reduction of 0,069 percent in the NOK/USD exchange rate. In addition, we see that the in-sample fit of the model, denoted by R^2, improves when the frequency is reduced.

The coefficient estimate in model (2) is however only significant at all levels using the daily frequency and at the 10 percent level when applying quarterly frequency. The results from this exercise are consistent with theory on the field. Suggesting that since Norway's export of oil is settled in U.S. Dollars, a lower income from the export would lead to a lower market demand for the Norwegian currency.

Table 1: *Regression results for model (1) and (2)*

NOK/USD	Daily	Weekly	Monthly	Quarterly
α	0,0039	0,0222	0,1093	0,4085
	(0,661)	-0,592	-0,515	(0,409)
ΔlnCRBR,t	-0,069	-0,086	-0,1204	-0,1454
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
R^2	0,0451	0,0784	0,1567	0,2477
α	0,0031	0,0141	0,0646	0,2425
	(0,733)	-0,744	-0,724	(0,667)
ΔlnCRBR,t-1	-0,0203	-0,0052	-0,0188	-0,0506
	(0,000)***	(0,546)	(0,295)	(0,094)*
R^2	0,0039	0,0003	0,0038	0,0301

Probabilities in parentheses: ***p<0,01, *** p<0,05, * p<0,10

6.2 The Contemporaneous model

In this subsection, we follow the procedure of Ferraro et al. (2015) to evaluate the predictability content between changes in the NOK/USD exchange rate and Crude Brent oil prices.

We again employ model (1) with contemporaneous oil price changes from section 6.1 and estimate the parameters through a rolling regression with several in-sample window sizes. It is important to notice that this is an ex-post forecast, where the predictive ability of the model is evaluated using realized changes of the oil price. Nevertheless, successful predictability of this model yields important inferences for practical use. That is, if we are able to find a sufficient model to predict the future price of oil, we can also produce good estimates of future exchange rates (Ferraro et al., 2015). The one-step-ahead pseudo out-of-sample forecast is given by

$$\Delta ex_{t+1}^{f} = \hat{\alpha} + \hat{\beta}\Delta p_{t+1} + u_t, \;\; t = R, R+1, \ldots, T-1$$

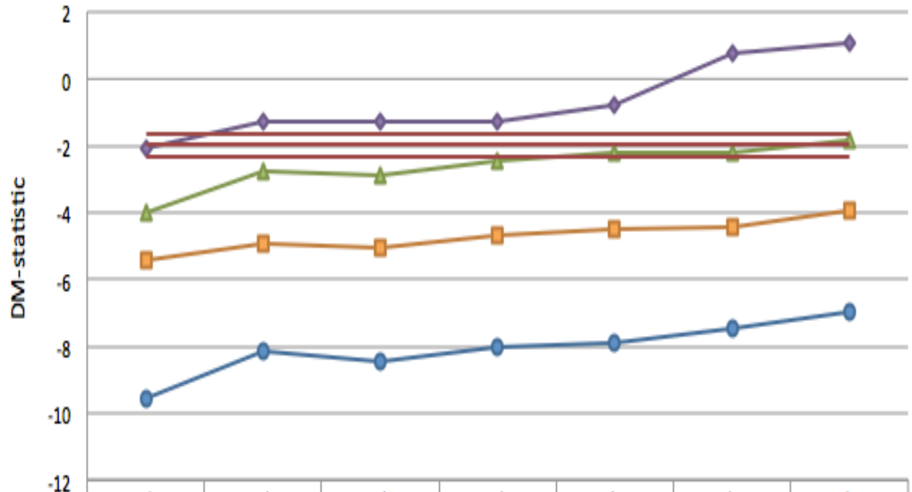
where $\hat{\alpha}$ and $\hat{\beta}$ are parameter estimates obtained from the rolling regression, R is the in-sample window size, and Δex_{t+1}^{f} is the one-step-ahead pseudo out-of-sample forecast. The realized change in Crude Brent oil prices is used in the above model as predictor for the change in the exchange rate. Not only is the rolling regression performed over several in-sample window sizes, we also perform this forecast for daily, weekly, monthly and quarterly frequencies. Finally, we compare our predictability to that of the random walk using Diebold and Mariano`s (1995) test.

6.2.1 Empirical results

Figure 4 below shows our results. When the Diebold and Mariano (1995) test statistic is below -1,645 we conclude that the oil price model significantly predicts the exchange rate better than the random walk at the 10% level. The test statistic is reported on the y-axis, and the in-sample window size related to the total sample size is reported on the x-axis. The three straight lines indicate the critical values where the level of significance increases from the highest to the lowest.

As can be seen from the negative test statistic, the test favors our model in all frequencies. For daily, weekly, and monthly datasets the test results are robust and significant independent of the in-sample window size. For quarterly frequency the test favors our model at all window sizes above 1/15. However, these results are only significant at the 5 percent level using the largest window size.

Comparing our findings with those from Ferraro et al. (2015) our results are more robust and significant in both daily and monthly data. Furthermore, they did not find significant results using the quarterly frequency. We also introduced a new frequency as suggested by Ferraro et al. (2015) and found highly robust and significant results. Full tables with p-values are reported in Appendix 1, table 1-4.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Daily	-9,544	-8,146	-8,463	-8,034	-7,915	-7,473	-6,976
Weekly	-5,429	-4,938	-5,033	-4,683	-4,476	-4,453	-3,936
Monthly	-3,999	-2,752	-2,871	-2,447	-2,192	-2,214	-1,843
Quarterly	-2,069	-1,297	-1,301	-1,301	-0,7516	0,7346	1,068
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

Fig 4: *DM-statistic for the contemporaneous model, reported at different in-sample window sizes of total sample size.*

6.3 The True forecasting model

In this subsection, we analyze the predictive ability for future change in the NOK/USD exchange rate using lagged changes in Crude Brent oil prices.

Again, we follow the procedure of Ferraro et al. (2015) but this time with what they call the true forecasting model. Although we established predictive content in the previous section, we now consider a stricter test to evaluate the actual forecast ability of lagged oil price changes on future changes in the exchange rate. We use model (2) from section 6.1 and employ rolling regressions with several in-sample window sizes in order to estimate the coefficients. The one-step-ahead pseudo out-of-sample forecast is then given by

$$\Delta ex_{t+1}^{f} = \hat{\alpha} + \hat{\beta}\Delta p_t + u_t, \;\; t = R, R+1, \dots, T-1$$

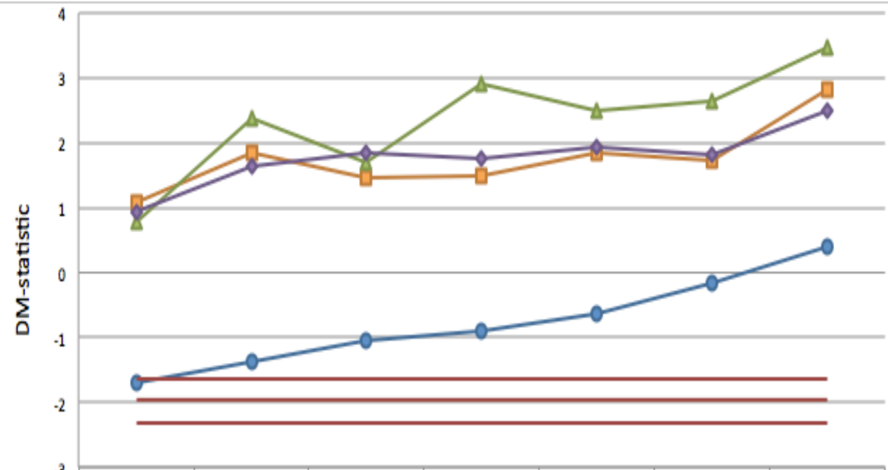
where $\hat{\alpha}$ and $\hat{\beta}$ are parameter estimates, R is the in-sample window size, and Δex_{t+1}^{f} is the one-step-ahead pseudo out-of-sample forecast for future change in the NOK/USD exchange rate. As before, we perform the test for all frequencies and compare our forecasts with those of the random walk using Diebold and Mariano`s (1995) test.

6.3.1 Empirical results

Our results are displayed in figure 5. First and foremost, we do find that lagged changes in the oil price are consistent and significant predictors of future changes in the exchange rate using daily frequency. The absence of similar evidence in previous literature makes this finding highly interesting. In addition, Ferraro et al. (2015) who performed the exact same analysis never outperformed the random walk when considering the average predictability over the out-of-sample forecast period. Indeed, they still conclude that short-horizon predictive ability never has convincingly been demonstrated at their high level of statistical significance. As previously mentioned Rogoff and Stavrakeva (2008) found that most of the popular exchange rate models from existing literature only outperform the random walk in one period of their sample. Therefore, our consistent result gives warranty to believe that the predictive relationship can be preserved in the future.

Although Diebold and Mariano`s (1995) test favors our model for almost all window sizes when using daily frequency it is important to notice that the null hypothesis of equal predictability between our model and the random walk can only be rejected at the 10 percent significance level when using ½ of total sample size as in-sample window for parameter estimation. However, as mentioned in section 5.3, the test statistic is concluded to be undersized by several influential studies, implying that the significant result we have is robust when compared to other test statistics.

For all other frequencies and window sizes we are never able to beat the random walk significantly. As a matter of fact, for all other frequencies, the test statistic is always positive and therefor suggesting lower predictability for our model compared to the random walk. Based on overall findings in this section we at this point reject the null of hypothesis 1, and conclude that there is significant evidence that oil prices can forecast exchange rates.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Daily	-1,707	-1,359	-1,059	-0,9069	-0,6285	-0,1615	0,401
Weekly	1,084	1,84	1,461	1,494	1,849	1,724	2,823
Monthly	0,7727	2,388	1,686	2,921	2,487	2,628	3,471
Quarterly	0,9426	1,638	1,832	1,752	1,92	1,813	2,492
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

Fig 5: *DM-statistic for the true forecasting model, reported at different in-sample window sizes of total sample size. Full tables with p-values reported in Appendix 2, table 5 – 8.*

7.0 Time varying exchange rate predictability

The previous analyses are based on models that assume constant model performance over time, and therefor results are based on overall predictability. However, because of the unstable economic environment there might be periods during our sample where either our model or the random walk perform significantly better than the other.

We employ the fluctuation test by Giacomini and Rossi (2010) to evaluate if there is time variation in the relative forecasting performance between our true forecasting model and the random walk. The test calculates rolling averages of the out-of-sample MSFE differences between our true forecasting model from the previous section and the random walk forecast over time. The null hypothesis is equal predictability between our model and the random walk. Similar to Ferraro et al. (2015) we employ the forecasts produced when using one half of the total sample size as in-sample window. For the rolling averages of out-of-sample MSFE differences we employ a window of 30 weeks. The test is performed on weekly, monthly, and quarterly frequencies. Since we have already found significant predictability in daily data for the entire sample, we do not consider this frequency for the test.

7.1 Empirical results

Figure 6 shows Giacomini and Rossi`s (2010) fluctuation test results when using weekly data. Negative values indicate that the test favors our model. When the test statistic is below the bottom blue line our forecasting model significantly outperforms the random walk at the 5 percent level.

From the figure we can see several periods with significant results in favor of our model. These are around 2008, between 2011 and 2012, and around 2013. Ferraro et al. (2015) who found that considering frequency of the data was important for capturing predictability suggested this frequency as further research. Our significant results therefore contribute with the possibility of longer horizon predictability. Monthly and quarterly figures are reported in Appendix 3, figure 1-2. They never forecast better than the random walk.

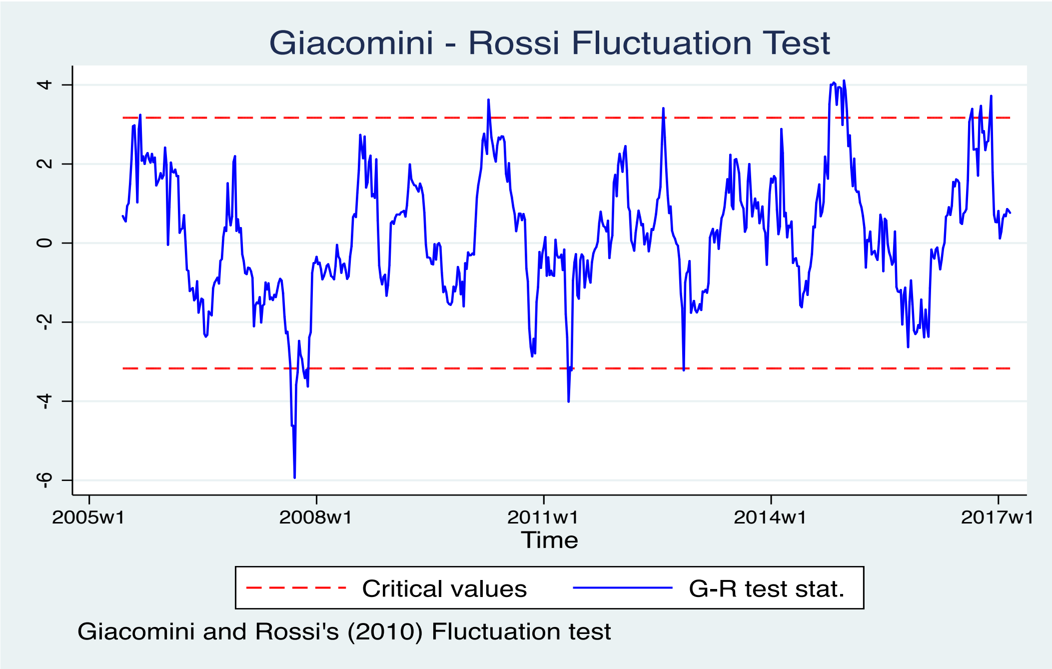


Fig 6: *Giacomini & Rossi`s (2010) fluctuation test with rolling DM-statistics for the true forecasting model using weekly data.*

8.0 Source of predictability

In subsection 6.3 we found significant predictability above existing literature in daily data. Also, compared to the research from Ferraro et al. (2015) who used the same true forecasting model with lagged changes in oil price as predictor for the exchange rate. In this section, we therefore analyze the source of our additional predictability by replicating the previous forecasting in two different exercises. First with the same sample length as Ferraro et al. (2015) and secondly with Crude WTI as benchmark for oil prices.

We find that the choice of benchmark for oil price is important and that Crude Brent is the correct type of oil to use in a Norwegian context.

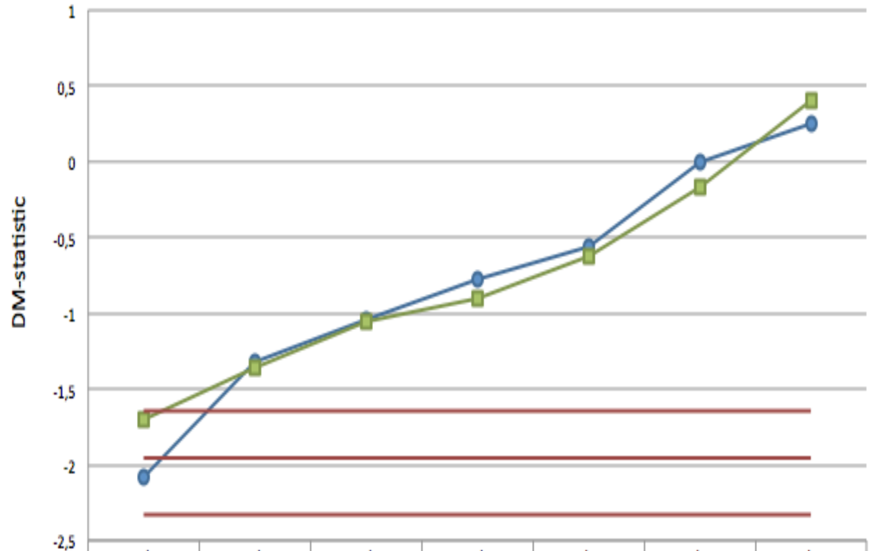
8.1 Extended sample length

Starting of we evaluate whether the extended sample length is the source for the additional predictive ability in the daily dataset. Therefore, we use the same sample length as Ferraro et al. (2015) for the true forecasting model in the previous section. That is, we use the same estimation technique as described in section 6.3 but with sample length between the 3rd of January 1994, and the 16th of September 2010.

8.1.1 Empirical results

Figure 7 below depicts our results with the Diebold and Mariano (1995) test statistic from comparing our forecast models with the forecast of the random walk. The blue line is the test statistic with reduced sample length and the green line is the test statistic from our original forecast.

Surprisingly, we find that the reduced sample length actually give us more robust result for the largest window size when using Crude Brent oil prices. In contrast to our extended sample size, the significance is now at the 5 percent level instead of the 10 percent level. We therefore conclude that the source of our additional predictability is not from the extended sample size.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Reduced sample lenght	-2,085	-1,324	-1,043	-0,7698	-0,5593	0,002	0,2548
Original sample lenght	-1,707	-1,359	-1,059	-0,9069	-0,6285	-0,1615	0,401
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

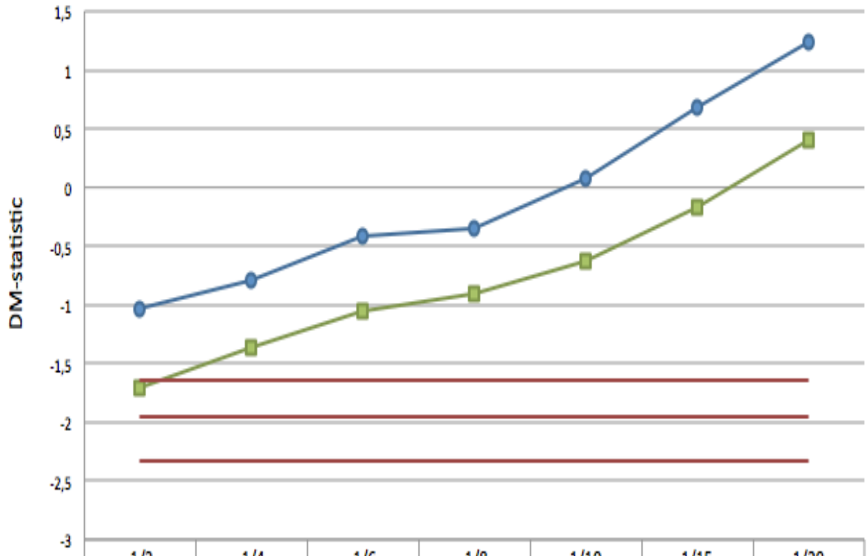
Fig 7:*DM-statistics for original sample length versus reduced sample length, for the true forecasting model.*

8.2 Choice of oil index

Further, we analyze the impact on the predictability of our choice to use the Brent oil price index. As mentioned in section 4, this proxy is more comparable to the Norwegian economy, since this is the type of crude oil being pumped from the Northern Sea. Although, the prices of Crude Brent and WTI has moved in tandem in decades, Chen, Huang and Yi (2015) found that a breakpoint occurred in 2010 which have lead to a persistent spread between the two prices. We still perform the same regression as described above but change the Crude Brent price index to the Crude WTI price index used in Ferraro et al. (2015). The sample length is our original from 1^{th} of January 1993 until 31^{st} of January 2017.

8.2.1 Empirical results

Figure 8 below shows our results. The Diebold and Mariano (1995) test statistic for comparing our forecast to the random walk using Crude WTI and Crude Brent is respectively illustrated by the blue and green line. The test statistic when using Crude WTI oil prices as predictor for the NOK/USD exchange rate yields less predictability for all in-sample window sizes. When using this benchmark we are never able to significantly beat the random walk with our forecast even with our longer time horizon. We therefore conclude that our choice of benchmark for oil is the source of our additional predictability and that using the correct benchmark for oil in a Norwegian context is crucial in order to successfully predict the NOK/USD exchange rate.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
WTI Benchmark	-1,032	-0,7985	-0,4105	-0,345	0,0802	0,6841	1,232
Brent Benchmark	-1,707	-1,359	-1,059	-0,9069	-0,6285	-0,1615	0,401
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

Fig 8: *DM-statistics for the Crude WTI oil benchmark versus the Crude Brent oil benchmark using the true forecasting model.*

9.0 Impact of the financial crisis

In August of 2007 the global financial crisis started to unveil in the U.S., as funds operating on US mortgage debt ceased activity. The crisis escalated, with major impact on the financial industry, seeing the bankruptcy of Lehman Brothers on September 15th, 2008. In the following period, the crisis became global and affected the economies of countries around the world.

Therefore, we want to investigate if the financial crisis had a disruptive impact on the predictability. During the period of 2007 until 2010, we find 15 out of the 30 most extreme values in our whole sample. According to Brooks (2014,

214) dummy variables may be justifiable used to remove observations corresponding to extreme events that are considered unlikely to be repeated. Given that there is such a significant number of extreme values in a short period of time, we find it relevant to include a test were these 15 values are removed. By removing these observations, we assume that the financial crisis did have an impact on the exchange rates for the given period. Hence, these observations are to be assumed that they are not a result of shifts in Crude Brent.

The extreme values were found by performing a standard OLS regression on daily data using model (2) from section 6.1. We thereafter collect the residuals and sort them from highest to lowest value. Figure 9, shows a time-series plot of the residuals and fitted values. From the graph we can see that there are several large outliers around the period of the financial crisis. All of the large outliers correspond to periods where the Norwegian Krone appreciated much more against the U.S. Dollar than we would have predicted.

Since we found that 15 of the 30 most extreme values were from the period of the financial crisis, dummy variables was created to remove these 15 observations from the total sample size of 6283 observations. We then performed the same out-of-sample forecasting with lagged oil prices as described in subsection 6.3. This test was also performed on weekly data.

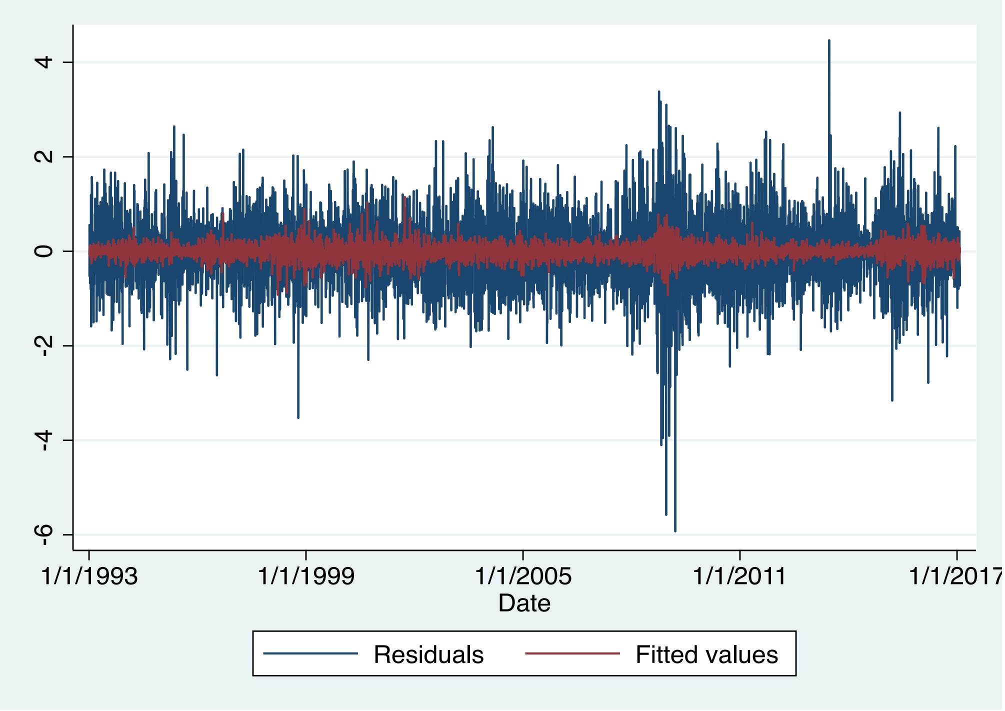
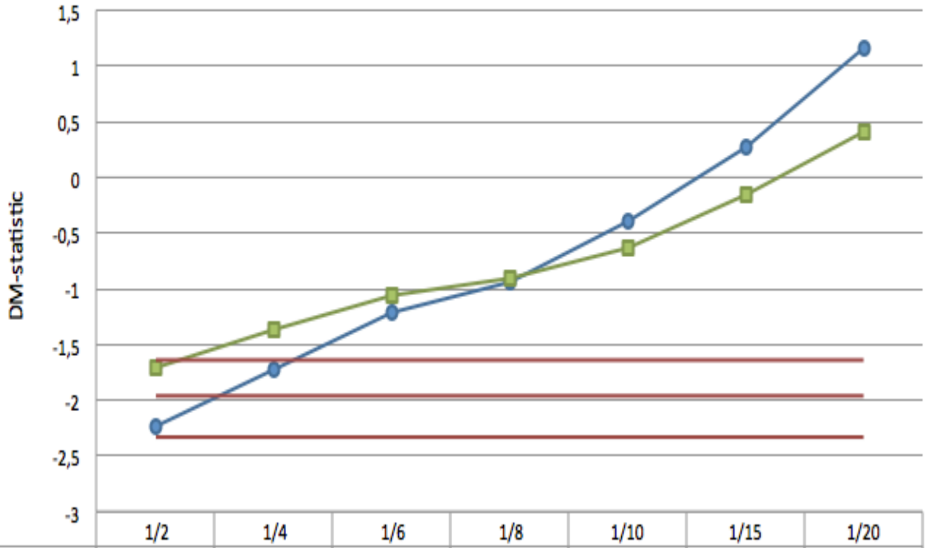


Fig 9: *Actual residuals from linear regression on natural log change against fitted values.*

9.1.Empirical results

Figure 10 shows the Diebold and Mariano (1995) test statistic from comparing our forecasts with the random walk. The blue line illustrates our results after removing the extreme values and the green line illustrates our original results. Findings shows that the out-of-sample forecast with removed extreme values have a higher predictability, and more robust result than the original forecast. Hence, our assumption that the financial crisis did have a disruption on the exchange rates for a short period is true, and that accounting for it may give a more accurate prediction. Based on our findings, we reject the null of hypothesis 2, that the financial crisis did not impact the exchange rate predictability. Appendix 5 shows results for weekly data, where we find no predictability improvement.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Reduced volatility	-2,233	-1,72	-1,217	-0,9451	-0,3925	0,2675	1,167
Original series	-1,707	-1,359	-1,059	-0,9069	-0,6285	-0,1615	0,401
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

Fig 10: *DM-statistics with and without extreme values from the financial crisis using the true forecasting model on daily data.*

10.0 Interest rate differentials

Focusing on the theory of interest rate differentials (IRD) as mentioned in section 2.3, we reconstruct the analysis preformed in section 6.2 using model (1), still applying the procedure of Ferraro et al. (2015), with a change of one variable. To perform the regression, Crude Brent is removed from the regression and the IRD of the NOK/USD exchange rate is added. The IRD is calculated by subtracting the U.S. interest rate from the Norwegian interest rate. The parameters are estimated through a rolling regression with several in-sample window sizes. Again, this is an ex-post forecast where the predictive ability of the model is evaluated using realized changes in the IRD. The one-step-ahead pseudo out-of-sample forecast is given by

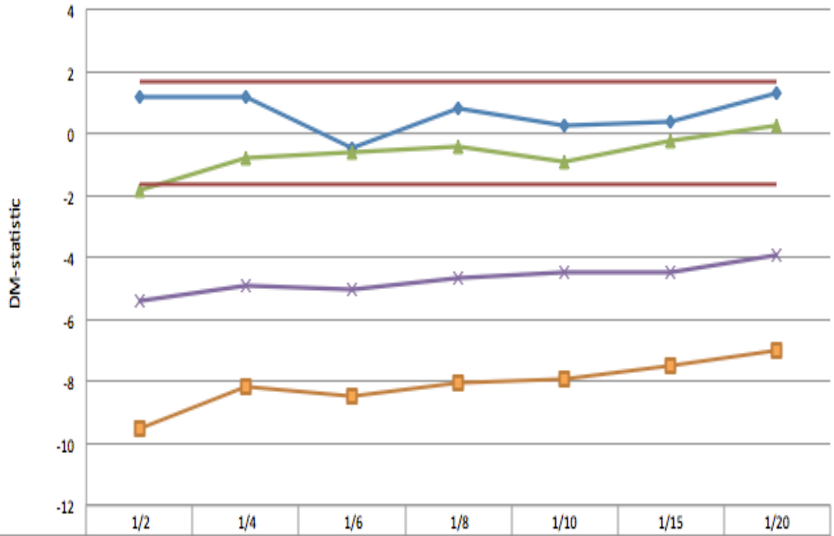
$$\Delta ex_{t+1}^{f} = \hat{\alpha} + \hat{\beta}\Delta IRD_{t+1} + u_t, \quad t = R, R+1, \ldots, T-1$$

where $\hat{\alpha}$ and $\hat{\beta}$ are parameter estimates obtained from the rolling regression, R is the in-sample window size, and ΔIRD_{t+1}^{f} is the one-step-ahead pseudo out-of-sample forecast. Again, we use several in-sample window sizes and perform the test using both daily and weekly data. Finally, we compare our predictability to that of the random walk using Diebold and Mariano`s (1995) test.

10.1 Empirical results

Our results are reported in figure 11, where the two red lines indicate critical values for the 10 percent significance level. When the Diebold and Mariano (1995) test statistic is below the bottom red line, our model significantly outperform the random walk. When the test statistic is above the top red line, the random walk has a significantly better forecast.

Although we do find predictability at the 10 percent significance level in favor of the model with interest rate differentials at one point, it never outperforms the oil-price model. For all other window sizes and frequencies, the results from the interest rate model are insignificant. Therefore, we keep the null of hypothesis 3 and concur with the findings of Meese and Rogoff (1988) that there is little evidence of a stable relationship between exchange rates and interest rates.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Daily IRD	1,168	1,172	-0,4729	0,8182	0,2572	0,3597	1,325
Daily Brent	-9,544	-8,146	-8,463	-8,034	-7,915	-7,473	-6,976
Weekly IRD	-1,833	-0,7685	-0,6002	-0,4279	-0,9202	-0,2679	0,2362
Weekly Brent	-5,429	-4,938	-5,033	-4,683	-4,476	-4,453	-3,936
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value RW (α=10%)	1,645	1,645	1,645	1,645	1,645	1,645	1,645

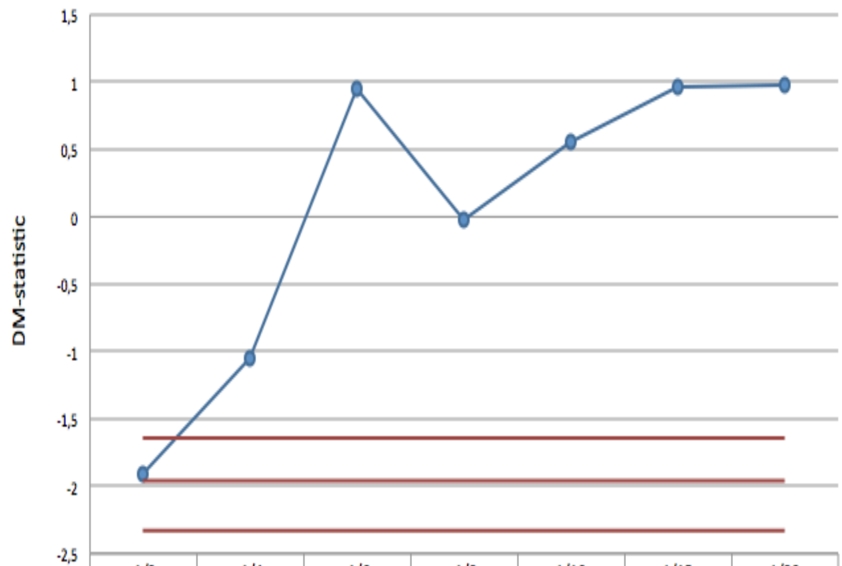
Fig 11: *DM-statistic for the contemporaneous model using change in IRD as predictor for the change in exchange rate compared with original results using daily and weekly data.*

11.0 Robustness check for the Dollar effect

Since the price of Crude Brent is quoted in U.S. Dollars and we evaluate the Norwegian Krone against the U.S. Dollar, there is a chance that there is a Dollar effect creating disruption in our results. To assess that our results are robust, we apply a test for the Dollar effect in similar matter as Ferraro et al. (2015) and Chen et al. (2010). We replicate the previous analysis performed in section 6.2, but instead use the logarithmic change in nominal NOK/GBP exchange rate as dependent variable. Otherwise the test is identical to the original with the exception that we only test for monthly data. We use monthly data to add robustness as it has low significance in previous tests.

11.1 Empirical results

We find significant results on a 5 percent level, with an in-sample window size of 1/2. This implies that our results are robust, since the predictive ability is present even if we use an exchange rate that does not involve the U.S. Dollar.



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
GBPNOK	-1,909	-1,049	0,9441	-0,0178	0,5495	0,96	0,9821
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33

Fig 12: *DM-statistics from the true forecasting model using changes in the Crude Brent price as predictor for changes in NOK/GBP exchange rate.*

12.0 Limitations

As the scope of this paper could be extensive, we have chosen certain limitations for this study. The limitations do open up for further research on the area.

This paper applies the period of January 1st 1993 to January 31st 2017. The Norwegian export of oil started in 1971. Therefore, an optimal timeline for the data sample would begin from that year in order to see the correlation and effect the oil export has had on the Norwegian Krone. Until 1993 the Norwegian Krone was pegged to different currencies, so it would require several variables to compensate for the pegging, which might not be significantly unbiased. Hence, we do not see that we can create variables that comprehend the pegging of the Norwegian Krone that was almost continuous since 1823 until the unpegging.

Furthermore, this paper does not take account for geopolitical affairs. Such as OPEC's attempts to influence the oil price, sanctions against major oil export nations like Russia and Iran, regional instability, war, climate change agreements and regulations. There is a chance that some geopolitical affairs have an impact that produces a shift in the oil price that could have an explanatory effect, but this we leave for future research.

Since 1990 until 2016 the export of oil in Norway has accounted for 39 % - 61 % of the country's total export (Oljedirektoratet, 2017). We expect that changes in the oil price should have a significant impact on the currency. Therefore, we have not weighted the commodity, nor have we included more of Norway's large exports, such as aquaculture, metals, weapons and chemicals. Our reasoning is that they represent a smaller percentage of the exports as singles than the oil export.

13.0 Conclusion

Our results show that Crude Brent oil prices have a robust and significant in-sample and out-of-sample fit relationship with NOK/USD exchange rates at daily, weekly, monthly and quarterly frequencies. The predictive power of contemporaneous realized oil prices are robust to the sample period under consideration and the choice of in-sample window size, with the exception of quarterly frequency where we only have significant predictability at the largest window.

When using lagged Crude Brent oil prices, the in-sample fit is highest at daily frequency. This is also related to the out-of-sample forecasting ability of daily lagged Crude Brent oil prices where we find a significant predictive ability at the highest in-sample window size. Also in this case, the predictive ability is consistent and robust for the sample period under consideration. At the weekly frequency the significant predictability are dependent on allowing for time-variation of the relative forecasting performance. Based on our results we conclude that there is significant evidence that oil prices can forecast exchange rates, and the null of hypothesis 1 is rejected.

In addition, we find that the choice of benchmark for oil price is important and that Crude Brent is the correct type of oil to use in a Norwegian context. Following the theoretical justification by Brooks (2014) we found that accounting for the financial crisis give more accurate prediction on short-horizons. Therefore, the null of hypothesis 2 is also rejected. Our findings are aligned with previous literature that interest rate differentials have no predictive ability on exchange rates and we keep the null of hypothesis 3. With this in mind, the answer to our research question is; yes, there is a significant connection between oil prices and exchange rates.

Our paper relates to existing literature of commodity prices and exchange rates. Commodity prices short-horizon predictive ability on exchange rates has never been demonstrated at a satisfactory level before and have only been evident during small periods. Our paper contributes with evidence that oil prices can in fact consistently and significantly predict currencies of major oil exporting countries. We also consider a new frequency where predictability is found when allowing for time-varying forecasting performance. Furthermore, we contribute with a new consideration to the literature, that choosing the correct benchmark for oil is important to detect predictability.

For further research, we suggest researching if our robust results using the Crude Brent benchmark can be transferred to other European currencies of oil-exporting countries.

References

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

Bjørk, L. H., Mork, K. A., & Uppstad, B. H. (1998). Påvirkes kursen på norske kroner av verdensprisen på olje? *Norsk Økonomisk Tidsskrift*, 1-33.

Brooks, Chris. 2014. *Introductory econometrics for finance.* 3rd ed. Cambridge University Press

Chen, Y. C., Rogoff, K. S., & Rossi, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics,* 125(3), 1145-1194. doi: 10.1162/qjec.2010.125.3.1145

Chen, W., Huang, Z., & Yi, Y. (2015). Is there a structural change in the persistence of WTI–Brent oil price spreads in the post-2010 period? *Economic Modelling*, 50, 64-71. doi: 10.1016/j.econmod.2015.06.007

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. doi: 10.1016/j.jimonfin.2005.08.002

Cheung, Y.-W., Lai, K. S., & Bergman, M. (2004). Dissecting the PPP puzzle: the unconventional roles of nominal exchange rate and price adjustments. *Journal of International Economics, 64*(1), 135-150. doi:10.1016/s0022-1996(03)00076-x

Chinn, M. D., & Meese, R. A. (1995). Banking on currency forecasts: How predictable is change in money? *Journal of International Economics,* 38(1), 161-178. doi: 0.1016/0022-1996(94)01334-O

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.

Diebold, F. X., & Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics,* 13, 253-265. doi: 10.2307/1392185

Diebold, F. X., & Nason, J. A. (1990). Nonparametric exchange rate prediction? *Journal of international Economics,* 28(3-4), 315-332.

Engel, C., Mark, N. C., & West, K. D. (2007). Exchange Rate Models Are Not as Bad as You Think. *NBER Macroeconomics annual*, 22, 381-473.

Engel, C., & West, K. D. (2005). Exchange rates and fundamentals. *Journal of political Economy*, *113*(3), 485-517. doi: 10.1086/429137

Faust, J., Rogers, J. H., & Wright, J. H. (2003). Exchange rate forecasting: the errors we've really made. *Journal of International Economics*, *60*(1), 35-59. doi: 10.1016/S0022-1996(02)00058-2

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

Frankel, J. A., & Rose, A. K. (1995). Empirical research on nominal exchange rates. *Handbook of international economics,* 3, 1689-1729.

Giacomini, R., & Rossi, B. (2010). Forecast comparisons in unstable environments. *Journal of Applied Econometrics*, 25(4), 595-620. doi: 0.1002/jae.1177

Giacomini, R., & White, H. (2006). Tests of conditional predictive ability. Econometrica, 74(6), 1545-1578. doi: 10.1111/j.1468-0262.2006.00718.x

Gourinchas, P. O., & Rey, H. (2007). International financial adjustment. *Journal of political economy*, 115(4), 665-703. doi: 10.1086/521966

Ince, O., Molodtsova, T., & Papell, D. H. (2016). Taylor rule deviations and out-of-sample exchange rate predictability. *Journal of International Money and Finance*, 69, 22-44. doi: 10.1016/j.jimonfin.2016.06.002

Kilian, L. (1999). Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? *Journal of Applied Econometrics,* 14(5), 491-510. doi: 10.1002/(SICI)1099-1255(199909/10)14:5<491::AID-JAE527>3.0.CO;2-D

Malkiel B.G. (2017). A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing. *Quantitative Finance,* 17(3), 327-330. doi: 10.1080/14697688.2016.1256598

Mark, N. C. (1995). Exchange rates and fundamentals: Evidence on long-horizon predictability. *The American Economic Review*, 201-218.

Meese, R. A., & Rogoff, K. (1983a). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of international economics,* 14(1-2), 3-24. doi: 10.1016/0022-1996(83)90017-X

Meese, R., & Rogoff, K. (1983b). The out-of-sample failure of empirical exchange rate models: sampling error or misspecification? In *Exchange rates and international macroeconomics* (pp. 67-112). University of Chicago Press.

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. doi: 10.2307/2328144

Norges Bank. *Pengepolitiske regimer I Norge etter 1816*. Retrieved from: http://www.norges-bank.no/globalassets/upload/pengepolitikk/historikk.pdf

Oljedirektoratet / Olje- og energidepartementet (2017) *Eksportverdier 1971-2016 Stoplediagram*. Retrieved from: http://www.norskpetroleum.no/produksjon-og-eksport/eksport-av-olje-og-gass/

Oslo Børs (2017) *Statoil*. Retrieved from: https://www.oslobors.no/markedsaktivitet/#/details/STL.OSE/overview

Rogoff, K. (1996). The purchasing power parity puzzle. *Journal of Economic literature*, *34*(2), 647-668.

Rogoff, K. S., & Stavrakeva, V. (2008). The continuing puzzle of short horizon exchange rate forecasting (No. w14071). *National Bureau of Economic Research.*

Rossi, B. (2006). Are exchange rates really random walks? Some evidence robust to parameter instability. *Macroeconomic dynamics*, 10(1), 20-38. doi: 10.1017/S136510050505008X

Rossi, B. (2013). Exchange rate predictability. *Journal of economic literature*, 51(4), 1063-1119.

Tideman, S., & Watson, M. W. (2003). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*, 41(3), 788-829. doi: 10.1257/002205103322436197

Yousefi, A., & Wirjanto, T. S. (2004). The empirical role of the exchange rate on the crude-oil price formation. *Energy Economics*, *26*(5), 783-799. doi: 10.1016/j.eneco.2004.06.001

West, K. D. (1996). Asymptotic inference about predictive ability. *Econometrica*, 64(5), 1067-1084. doi: 10.2307/2171956

Appendices

Appendix 1: Full tables for contemporaneous model at daily, weekly, monthly, and quarterly frequencies

Table 1:

Contemporaneous model. Forecasting ability in daily data between 4th of January 1994 and, 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	1006	(0,000)***	-5,869
3/4	943	(0,000)***	-7,848
1/2	629	(0,000)***	-9,544
1/4	314	(0,000)***	-8,146
1/6	210	(0,000)***	-8,463
1/8	157	(0,000)***	-8,034
1/10	126	(0,000)***	-7,915
1/15	84	(0,000)***	-7,473
1/20	63	(0,000)***	-6,976

Table 2:

Contemporaneous model. Forecasting ability in weekly data between 4th of January 1994 and, 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	1006	(0,0065)***	-2,723
3/4	943	(0,0004)***	-3,563
1/2	629	(0,0000)***	-5,429
1/4	314	(0,0000)***	-4,938
1/6	210	(0,0000)***	-5,033
1/8	157	(0,0000)***	-4,683
1/10	126	(0,0000)***	-4,476
1/15	84	(0,0000)***	-4,453
1/20	63	(0,0001)***	-3,936

Table 3:

Contemporaneous model. Forecasting ability in weekly data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	231	(0,0030)***	-2,963
3/4	216	(0,0002)***	-3,769
1/2	145	(0,0001)***	-3,999
1/4	72	(0,0059)***	-2,752
1/6	48	(0,0041)***	-2,871
1/8	36	(0,0144)**	-2,447
1/10	29	(0,0248)**	-2,192
1/15	19	(0,0268)**	-2,214
1/20	14	(0,0653)*	-1,843

Table 4:

Contemporaneous model. Forecasting ability in weekly data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	77	(0,1338)	-1,499
3/4	72	(0,0819)*	-1,74
1/2	48	(0,0386)**	-2,069
1/4	24	(0,1947)	-1,297
1/6	16	(0,1933)	-1,301
1/8	12	(0,1931)	-1,301
1/10	10	(0,4523)	-0,7516
1/15	6	(0,4626)	0,7346
1/20	5	(0,2854)	1,068

Appendix 2: Full tables for lagged model at daily, weekly, monthly, and quarterly frequencies

Table 5:

Lagged model. Forecasting ability in daily data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	5026	(0,4802)	-0,7061
3/4	4712	(0,3765)	-0,8843
1/2	3140	(0,0878)*	-1,707
1/4	1571	(0,1742)	-1,359
1/6	1047	(0,2897)	-1,059
1/8	785	(0,3644)	-0,9069
1/10	628	(0,5297)	-0,6285
1/15	419	(0,8717)	-0,1615
1/20	314	(0,6885)	0,401

Table 6:

Lagged model. Forecasting ability in weekly data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	1006	(0,7015)	-0,3833
3/4	943	(0,1883)	0,8506
1/2	629	(0,2783)	1,084
1/4	314	(0,0658)*	1,84
1/6	210	(0,1440)	1,461
1/8	157	(0,1352)	1,494
1/10	126	(0,0645)*	1,849
1/15	84	(0,0846)*	1,724
1/20	63	(0,0048)***	2,823

Table 7:

Lagged model. Forecasting ability in monthly data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	231	(0,9139)	0,1082
3/4	216	(0,7472)	0,3223
1/2	145	(0,4397)	0,7727
1/4	72	(0,0170)**	2,388
1/6	48	(0,0917)*	1,686)
1/8	36	(0,0035)***	2,921
1/10	29	(0,0129)**	2,487
1/15	19	(0,0086)***	2,628
1/20	14	(0,0005)***	3,471

Table 8:

Lagged model. Forecasting ability in quarterly data between 4th of January 1994, and 31st of January 2017

In-sample window size	In-sample window	P-value	DM-statistic
4/5	77	(0,7033)	-0,3809
3/4	72	(0,5083)	-0,6615
1/2	48	(0,3459)	0,9426
1/4	24	(0,1015)	1,638
1/6	16	(0,0670)*	1,832
1/8	12	(0,0798)*	1,752
1/10	10	(0,0549)*	1,92
1/15	6	(0,0699)*	1,813
1/20	5	(0,0127)**	2,492

Appendix 3: Fluctuation test for monthly and quarterly data

Fig1: Monthly. True forecasting model.

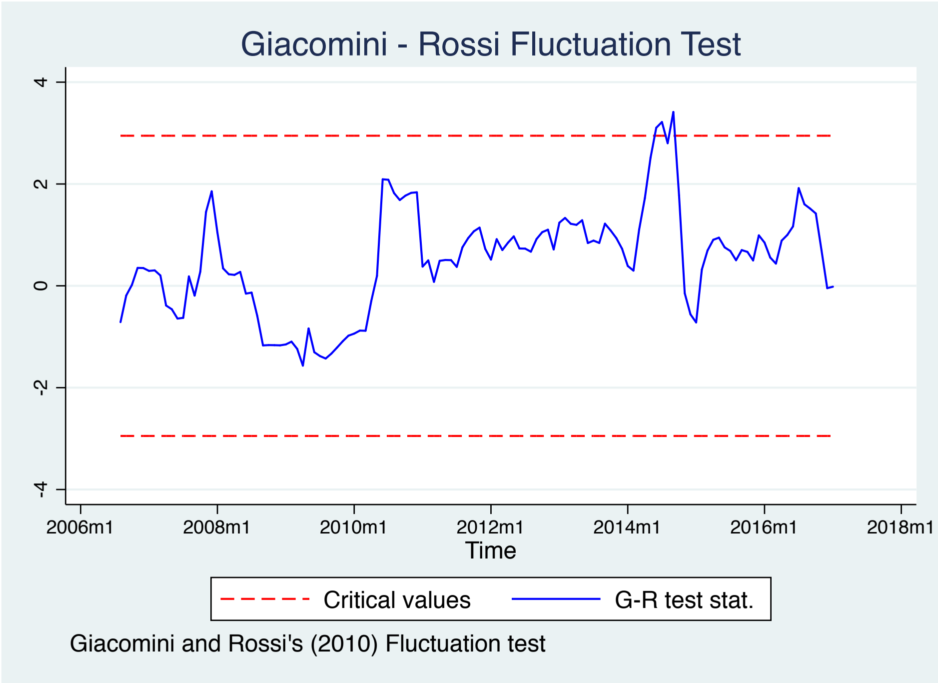
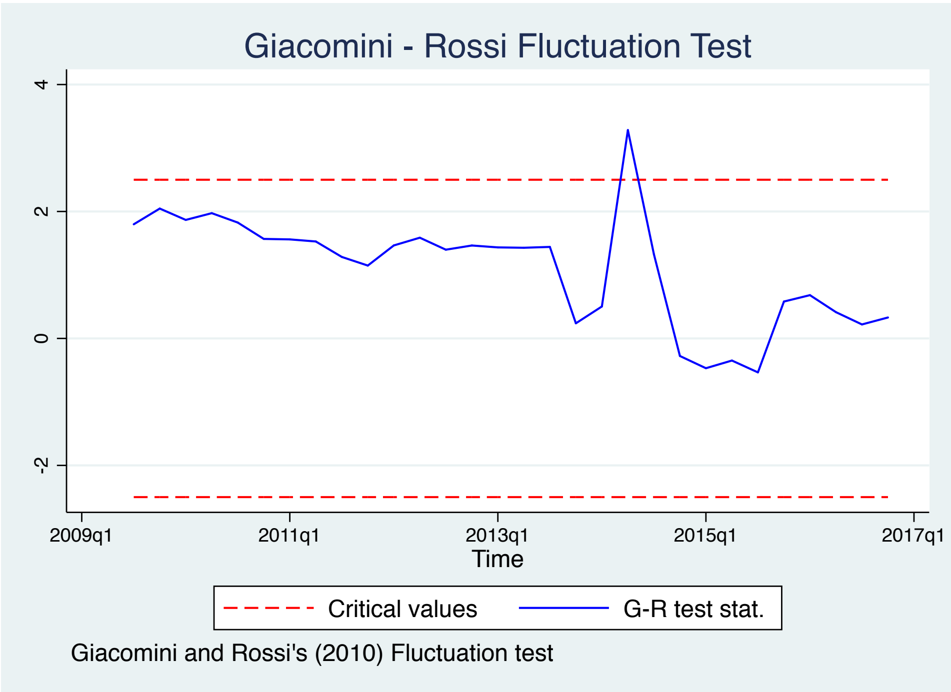


Fig: 2

Quarterly. True forecasting model.



Appendix 4: Full tables. Source of predictability

Table 9:

True forecasting model. Reduced sample length versus original sample length.

In-sample window size	In-sample window	P-value	DM-statistic
4/5	3487	(0,0223)**	-2,284
3/4	3269	(0,0173)**	-2,38
1/2	2180	(0,0371)**	-2,085
1/4	1090	(0,1854)	-1,324
1/6	727	(0,2970)	-1,043
1/8	545	(0,4414)	-0,7698
1/10	436	(0,5760)	-0,5593
1/15	291	(0,9981)	0,002
1/20	218	(0,7989)	0,2548

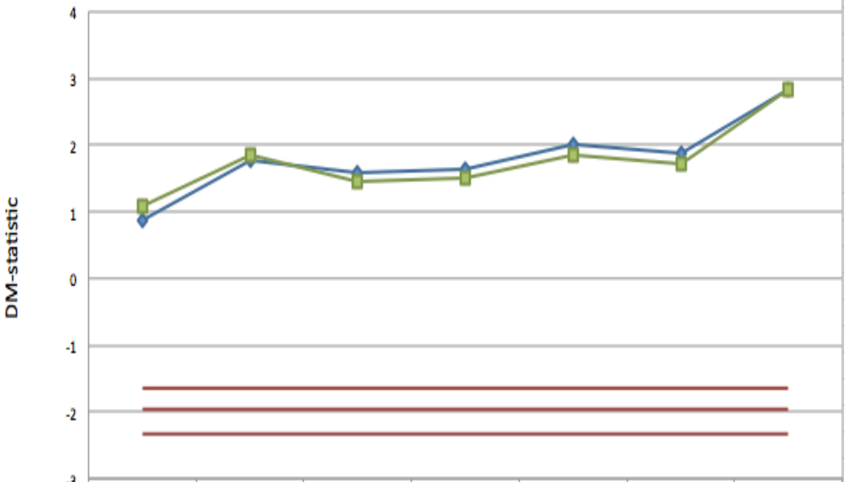
Table 10:

True forecasting model. WTI Benchmark versus Brent Benchmark.

In-sample window size	In-sample window	P-value	DM-statistic
4/5	5026	(0,8870)	0,1421
3/4	4712	(0,8458)	-0,1945
1/2	3140	(0,3022)	-1,032
1/4	1571	(0,4246)	-0,7985
1/6	1047	(0,6814)	-0,4105
1/8	785	(0,7301)	-0,345
1/10	628	(0,9361)	0,0802
1/15	419	(0,4939)	0,6841
1/20	314	(0,2179)	1,232

Appendix 5: *Impact of financial crisis on predicatbility, weekly data.*

Weekly data true forecasting model



	1/2	1/4	1/6	1/8	1/10	1/15	1/20
Reduced volatility	0,8731	1,763	1,591	1,65	2,003	1,888	2,834
Original series	1,084	1,84	1,461	1,494	1,849	1,724	2,823
Critical value (α=10%)	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645	-1,645
Critical value(α=5%)	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96	-1,96
Critical value (α=1%)	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33	-2,33