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Can Taylor Rule Fundamentals Predict the USD/NOK Exchange Rate?

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Abstract

The objective of this paper is to offer new insight to the exchange rate literature by examining the predictability of the USD/NOK exchange rate. Using Taylor rule fundamentals as a predictor, we examine exchange rate predictability in the period from August 2001 to February 2015. We construct 32 models on the basis of Taylor rule, and compare their forecasting ability with the random walk. Our results suggest that an asymmetric model with interest rate smoothing, heterogeneous coefficients and a constant outperforms the random walk.

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1. Introduction

The objective of this paper is to offer new insight to the exchange rate literature by examining the predictability of the USD/NOK exchange rate.

The exchange rate literature has been concerned about exchange rate predictability ever since Meese and Rogoff introduced their famous puzzle in 1983. Meese and Rogoff examined the out-of-sample performance of economic models during the post-Bretton Woods period and found that they do not perform better than a random walk model. It is therefore reasonable to ask if exchange rates actually are predictable? The consensus in the literature seems to be that "it depends". The choice of the predictor, the sample period chosen and the forecast evaluation method proves to have strong impacts on the results.

The choice of predictors for exchange rate models is essential, and most studies have used traditional predictors like interest rate differentials, price and inflation differentials and money, output and productivity differentials. Traditional predictors does occasionally find evidence of predictability, like in the work by Clark and West (2006), who find out-of-sample predictability by Uncovered Interest Rate Parity (UIRP). However, most studies that use traditional predictors do not find evidence that the models significantly outperform the random walk.

Alternative predictors like external imbalance measures and commodity prices have also been introduced. Gourinchas and Rey (2007) and Della Corte, Sarno and Sestieri (2012), find that the net foreign asset model has a higher ability to predict exchange rates than a random walk, at least at short horizons. On the other hand, Chen and Rogoff (2003), and Chen, Rogoff and Rossi (2010) focus on commodity prices as the fundamental when examining countries with high export of commodities. The evidence, using commodity prices as predictor, is varying. While there is some evidence of in-sample fit, the out-of-sample performance depends on the choice of sample and the frequency of the data.

The models that have shown to have the highest level of out-of-sample forecasting ability, is the models that incorporate Taylor rule fundamentals. The main idea behind the Taylor rule fundamentals model is to consider two economies that both set their interest rates according to a Taylor type rule. By uncovered interest rate parity their exchange rate will reflect their relative interest rates. Further, as a consequence of both countries setting their interest rate according to a Taylor type rule, their output gaps and their inflation levels will be reflected. According to this theory the interest rate differential should be the best predictor for the exchange rate. However, this turns out not to be the case. Therefore, it is essential to find an explanation for why Taylor rule fundamentals provide a higher forecasting ability than the UIRP.

By using Taylor rule fundamentals Molodtsova and Papell (2009) find evidence of short-term predictability for 11 out of 12 currencies vis-a-vis the US dollar over the post-Bretton Woods float. This provides us with argumentation for using Taylor rule for out-of-sample exchange rate predictability, as it has more out-of-sample predictive content (Rossi, 2013). Secondly, literature argues that linear models are the most successful models for exchange rate predictability (Rossi, 2013). For monetary fundamentals the use of real-time rather than reserved data can affect predictive ability. However, for Taylor rule fundamentals this is less a concern, hence an argument for choosing Taylor rule (Rossi, 2013).

None of the existing models presented above support exchange rate forecasting ability across all countries and all sample periods. Interestingly, there has not been much research on the USD/NOK exchange rate. Former research on exchange rate predictability has shown that the choice of country is essential for the results, therefore, we find it interesting to examine the USD/NOK exchange rate. Studies that apply Taylor rule fundamentals as the predictor have provided evidence of short-term predictability in several countries, and this has captured our attention. Therefore, our research paper aims to answer if Taylor rule fundamentals can tell us something about the predictability of the USD/NOK exchange rate. Hence, our research question is:

"Can Taylor rule fundamentals predict the USD/NOK exchange rate?"

This research paper is strongly motivated by the research of Molodtsova and Papell (2009). The Taylor rule fundamentals models that we develop will be in line with their research, and we also wish to examine the performance of the traditional predictor, uncovered interest rate parity. Further, we assess the significance of the forecast performance via an out-of-sample predictability test, instead of an in-sample test that examines if the lagged predictor has explanatory power for exchange rates over the full sample. The out-of-sample tests are the most challenging to beat, and consequently is the most frequently used choice of test. The performances of the two models are then compared to a benchmark model, the random walk. Furthermore, comparing their relative root mean squared error examines their overall forecasting ability.

The decision to examine the predictability of the USD/NOK exchange rate is based on three arguments. First of all, we find it interesting to examine an exchange rate that has little existing research. Secondly, as we wish to follow in line with Molodtsova and Papell (2009), and the consensus in the literature, we use the United States (US) as the base country. This provides us with the opportunity to discuss our findings relative to other studies. Thirdly, exchange rate projections are especially important for central banks of countries that are heavy importers or exporters of commodities (Rossi, 2013). This accounts for both Norway and the US, and the two nations are connected through both trade and politics. The United States and Norway have a long history of friendly interactions, and the Norwegian economy is reliant on the development in the United States. In 2015 Norway exported goods to the US for an amount of 32.2 Billions NOK, and consequently the US is among Norway's top export destinations (SSB, 2016). Norway's Government Pension Fund - Global, which is essential for the Norwegian economy, has placed nearly 35% of its investments in the United States (Regjeringen, 2014).

In 2015 the US was ranked as the largest oil producer in the world, while Norway ranked as number 14. The trade in services between the two countries, including both export and imports, totalled at 5.4 billion dollars in 2012 (United States Trade Representative, 2014). Being an oil exporting country, the Norwegian economy relies heavily on oil, and falling oil prices will subsequently put pressure on the Norwegian currency. The US is also influenced by oil prices, however, great economic diversity reduces the impact on the US dollar. All in all, examining the predictability of exchange rate movements between two currencies that are heavily dependent on import and export is interesting, and we hope that our research question will provide us with insight on the topic.

The structure of the thesis is as follows; chapter two introduces the theoretical framework, which provides the basis for our research. Furthermore, chapter three contains a literature review, introducing and discussing former research on the topic. Then, chapter four and five contains the empirical framework and considers the data we will be using in our study. In chapter six the results will be presented, followed by a discussion of the results in chapter seven. The thesis will be completed with a short conclusion in chapter eight.

2. Theoretical Framework

In this section we present theories and ideas that create the foundation for our research, particularly the Taylor rule, uncovered interest rate parity and the forward premium puzzle.

2.1 Taylor Rule

The main building block for the development of our exchange rate models is the Taylor rule for monetary policy, introduced by Taylor in 1993 (Taylor, 1993). There is consensus in literature that Taylor rule fundamentals have better out-of-sample predictive content than traditional economic predictors (Rossi, 2013). Additionally, we wish to follow in the steps of Molodtsova and Papell (2009) and therefore justify the use of Taylor rule fundamentals as our research basis.

The monetary policy rule can according to Taylor (1993) be specified as:

$$i_t^* = \pi_t + \phi(\pi_t - \pi^*) + \gamma y_t + r^* \ , \qquad (2.1)$$

where all variables are specified in log form, and i_t^* is the target for the short-term interest rate, π_t is the inflation rate, π^* is the target level of inflation, y_t is the output gap or percent deviation of actual Gross Domestic Product (GDP) from an estimate of potential level, and r^* is the long-run equilibrium level of the real interest rate. If inflation rises above the target level, and/or output is above potential output, the central bank will according to Taylor rule raise the short-term nominal interest rate.

The main idea that Taylor developed is that monetary authorities set the nominal interest rate as a function of inflation, how the inflation differs from the inflation target, the output gap and the real interest rate. Hence, when there is high inflation in a country, the central bank will increase the interest rate. If output is lower than potential output, a more expansionary monetary policy will be conducted (Rossi, 2013). The Taylor rule provides a guideline for the central bank, so that the interest rate can be set in response to changes in the economic variables. It is generally believed that deflation is much worse for an economy than low inflation, therefore the target level of inflation is positive. According to the natural rate hypothesis, output can not permanently exceed potential output; therefore, the target level of the output deviation from natural rate y_t is zero (Molodtsova and Papell, 2009).

2.2 Uncovered Interest Rate Parity (UIRP)

Uncovered Interest Rate Parity (UIRP) serves as the base when we develop the Taylor rule fundamentals model for exchange rates. Fisher founded UIRP in 1896. He developed a condition where the difference between interest rates, expressed in two countries' currencies, is equal to the expected change in the exchange rate (Dimand, 1999).

UIRP states that the interest differential between two countries is equal to the expected change in the exchange rate between two countries' currencies. The UIRP is derived as:

$$(1 + i_{t+h}) = (1 + \tilde{\imath}_{t+h}) E_t(S_{t+h}/S_t) \ , \tag{2.2}$$

where the expectations at time t is denoted $E_t(.)$. The nominal exchange rate is denoted S_t, and gives the price of foreign currency in terms of domestic currency at time t. While, S_{t+h} is the nominal exchange rate at time t+h, where h is the horizon. In a world with perfect foresight, investors can buy $1/S_t$ units of foreign bonds using one unit of home currency (Rossi, 2013). The foreign bond will pay one unit plus the foreign interest rate, therefore the return converted back to domestic currency will equal $S_{t+h}(1 + \tilde{\imath}_{t+h})/S_t$ in expectations. This return should in expectation be equal to the return the principal receives from investing in the domestic bond, which is $1 + i_t$. By setting these two equal to each other, we derive the UIRP, where "~" denotes foreign variables.

Further, by taking the first order log linear approximation of equation (2.2), the UIRP can be written as:

$$E_t(s_{t+h} - s_t) = \alpha + \beta(i_{t+h} - \tilde{\imath}_{t+h}) \ , \qquad (2.3)$$

where $s_t = ln\,(S_t)$, and the term $E_t(s_{t+h} - s_t)$ is the approximated expected change in exchange rate. Further, for the UIRP to hold the constant α must be zero, and the intercept β must be one. UIRP is an equilibrium condition in which investors are indifferent between which bond to invest in, foreign or domestic. If the UIRP hold the choice of investment should not matter for the investor.

2.3 Forward Premium Puzzle

The forward premium puzzle is connected to the collapse of the UIRP. The forward premium is defined as the difference between the spot rate and the forward rate, and the premium is positive when the forward rate exceeds the spot rate. By UIRP and assuming that covered interest parity holds, the interest rate differential should be a perfect predictor of the change in exchange rate. However, the puzzle is developed because the forward rate does not give an unbiased prediction of the future spot rate (Chinn, 2007). A suitable starting point when discussing the forward premium puzzle, is to investigate whether the forward rate, F_t, is equal to the expected value of the future spot rate, (S_{t+1}):

$$F_t = E_t(S_{t+1}) \qquad (2.4)$$

An extensive amount of research finds that the forward rate is an unbiased estimate of the future spot rate. Therefore, agents can earn profits by speculating in forward foreign exchange rate. The condition implies that the expected domestic currency profit is zero, while expected foreign currency profit is not, causing a problem.

Following the forward premium puzzle, a positive interest rate differential produces forecasts of exchange rate appreciation, in contrast to the UIRP where a positive interest rate differential gives forecasts of exchange rate depreciation (Molodtsova and Papell, 2009). Hence, UIRP states that the domestic currency is expected to depreciate when the domestic nominal interest rate exceeds the foreign nominal interest rate (Bansal and Dahlquist, 2000). Given a positive forward premium, exchange rate appreciation is predicted, which is in contrast to theory that predict depreciation (Gourinchas and Tornell, 2004). The puzzle suggests that the nominal interest differentials predict the opposite effect as UIRP.

Siegel's paradox suggests that UIRP is violated, indicating that something with UIRP must be fundamentally wrong. If UIRP holds a domestic investor would be indifferent between investing in own or foreign currency. By rewriting UIRP from equation (2.2), for the domestic investor we will have that:

$$\frac{1+i_{t+h}}{1+\tilde{i}_{t+h}} = E_t\left(\frac{S_{t+h}}{S_t}\right) = \frac{1}{S_t}\ E_t(S_{t+h}) \ , \qquad (2.5)$$

and following UIRP, for the foreign investor we have that:

$$\frac{1+\tilde{i}_{t+h}}{1+i_{t+h}} = E_t\left(\frac{1/S_{t+h}}{1/S_t}\right) = E_t\left(\frac{S_t}{S_{t+h}}\right) \ , \qquad (2.6)$$

which can be converted in the terms of investing in domestic currency, so that equation (2.6) can be expressed as:

$$\frac{1+i_{t+h}}{1+\tilde{i}_{t+h}} = \frac{1}{S_t}\ \frac{1}{E_t(1/S_{t+h})} \ . \qquad (2.7)$$

From these equations we observe that the right hand side of equation (2.5) should be equal to the right hand side of equation (2.7). By doing so we get:

$$\frac{1}{E_t(1/S_{t+h})} = E_t(S_{t+h}) \ . \qquad (2.8)$$

This equilibrium can not hold in expectations. Equation (2.8) is connected to Jensen´s inequality, which states that the right hand side exceeds the left hand side. This is the base of Siegel’s paradox. Siegel's paradox states that the forward rate of the foreign currency should be equal to the expected foreign-domestic exchange rate. The paradox is that foreign investors only care about own currency return, and at the same time risk-neutral domestic investors only care about their currency returns (Obstfeld and Rogoff, 1996). Following the paradox, for the equilibrium to hold there must exist a risk premium. Empirical evidence put forward by Hodrick (1987) and more recent studies, points out that the log forward rate is not equal to the expected value of the future log spot rate. Notably, realized exchange rate changes goes in the opposite direction of what is predicted by the forward premium. This suggests that it is possible to make profits from betting against the forward rate (Obstfeld and Rogoff, 1996).

3. Literature Review

Explaining exchange rate behaviour with open-economy macro theory using economic fundamentals has proven to be challenging (Molodtsova and Papell, 2009). Predicting exchange rate behaviour has been frequently studied ever since Meese and Rogoff in 1983 examined three out of sample exchange rate models during the post-Bretton Woods period, and found that none performed better than the random walk (Meese and Rogoff, 1983).

In the recent years, there has been a comprehensive amount of literature connecting Taylor rule fundamentals to exchange rate predictability. Several studies have found evidence of predictability when looking at longer horizons, starting with Mark (1995). Furthermore, Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) evaluate the out of sample-predictability of the US dollar/Deutsche Mark nominal exchange rate from 1979 to 1998. They find that predictability increases when using real-time data, that is, data that was available at the time the central bank made their decisions. Furthermore, they find higher predictability with models that only include inflation and output coefficients in the central banks reaction functions, and allowing for the exchange rate in the Bundesbank reaction function.

Molodtsova and Papell (2009) also examine out-of-sample predictability with Taylor rule fundamentals for 12 OECD countries vis-a-vis the United states from 1973 to 2006. They find evidence of short-term predictability for 11 out of 12 countries by using quasi-real time data, and their strongest evidence arrives from incorporating heterogeneous coefficients and interest rate smoothing. Furthermore, Molodtsova, Nikolsko-Rzhevskyy and Papell (2011) find that the variables that are included in central bank´s Taylor rule can have forecasting ability for the USD/EUR exchange rate from 1999-2007, and Mark and Sul (2001) find evidence that monetary fundamentals provide evidence of predictability for 13 of 18 exchange rates.

Evidence on predictability in the exchange rate literature has shown to be dependent on the type of predictor, the sample, the choice of country and the forecast evaluation method. Kilian (1999) serves as a suitable illustration of this. He argues that the finding of increased long-horizon predictability is more likely related to distortions, not power gains. Kilians paper re-examines the data set from Mark (1995), and find only weak evidence that monetary fundamentals differences provide exchange rate predictability.

When it comes to examining the performance of interest rate parity, monetary and productivity based models, Cheung, Chinn and Pascual (2005) find that none of these models outperform a random walk. However, they do find that at long horizons UIRP forecasts better than the random walk, even though their finding is never significant. Molodtsova and Papell (2009) also find that models that include interest rate fundamentals provide weaker evidence of predictability than Taylor rule fundamentals models.

The most successful predictor in exchange rate literature, aside from Taylor rule fundamentals, is using net foreign asset positions. The main idea is that when a country experiences a current account imbalance, a depreciation of the country's currency will restore the balance between the country and the rest of the world (Gourinchas and Rey, 2007). The adjustment in the currency serves as a wealth transfer between the domestic country and the rest of the world, and by this line of thought, a country's net foreign asset positions can serve as an exchange rate predictor. Studies like Alquist and Chinn (2008), Gourinchas and Rey (2007) and Della Corte, Sarno and Sesteri (2012) all find out-of-sample predictability both at long and short horizons, when net foreign assets (NXA) serves as the predictor.

4. Empirical Framework

This section introduces the empirical framework of our study. First, we present the Taylor rule fundamentals model with different specifications. Second, we introduce the interest rate fundamentals model. Lastly, we present our forecast evaluation method.

4.1 Taylor Rule Fundamentals model

In this paper we will use the linear Taylor rule model of exchange rate determination as a starting point. Furthermore, we take different specifications into account so that an equation for exchange rate predictability can be developed. The core idea of the Taylor rule fundamentals model is that if two countries set their interest rates according to Taylor rule, following UIRP, the exchange rate will reflect their interest rates, subsequently also their output gaps and inflation rate (Rossi, 2013). If this was accurate, the interest rate differential should be the perfect predictor. However, since the model builds on UIRP, and empirical evidence suggests that UIRP does not hold in reality, it is surprising that this model holds (Chinn, 2008). Taking this into consideration, we follow Molodtsova and Papell (2009) and take several assumptions into account and reverse all of the signs so that UIRP is not incorporated directly into the model.

By rewriting equation (2.1), we have that:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t \ , \qquad (4.1)$$

where the constant term μ is a combination of the parameters π^* and r^*. Furthermore, $\lambda = 1 + \phi$, where λ is larger than one. Hence, the Taylor principle is satisfied since a rise in inflation will be followed by an increase in the real interest rate.

The real exchange rate, q_t, can be included in (4.1), which yields:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t + \delta q_t \quad , \tag{4.2}$$

where the real exchange rate is defined as:

$$q_t = s_t - p_t + \tilde{p}_t \quad , \tag{4.3}$$

where q_t is the log of the real exchange rate, s_t is the log of the nominal exchange rate, p_t is the log of the domestic price level and $\tilde{p}_t$ is the log of the foreign price level.

Clarida, Gali and Gertler (1998), (hereafter CGG), argues that δ in equation (4.2), equals zero for the US. This implies that the real exchange rate is not included in the monetary policy rule for the US. However, they find it reasonable to include the real exchange rate for other countries. Molodtsova and Papell (2009) argue that the rationale for including the real exchange rate is that the central bank wants to keep the nominal exchange rate at the Purchasing Power Parity level (PPP). If the exchange rate depreciates, the central bank will increase the interest rate to make PPP hold.

Following CGG we also postulate a variant of the Taylor rule where the interest rate can partially adjust to the target:

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + v_t \quad , \tag{4.4}$$

where i_t represent the interest rate, i_{t-1} is the lagged interest rate, and ρ is defined as the interest rate smoothing parameter. If ρ equals one, this implies that the interest rate at time t is a function of the interest rate at time t-1. Further, v_t is the error term.

Combining equation (4.2) and (4.4) leads to the following equation:

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t + \delta q_t) + \rho i_{t-1} + v_t \quad , \tag{4.5}$$

where we as mentioned assume that $\delta = 0$ for the US.

In order to create the Taylor rule forecasting equation, we first derive the interest rate differential. This is obtained by subtracting the interest rate reaction function for Norway, from the interest rate reaction function for the US:

$$i_t - \tilde{i}_t = \alpha + \alpha_{u\pi}\pi_t - \alpha_{f\pi}\tilde{\pi}_t + \alpha_{uy}y_t - \alpha_{fy}\tilde{y}_t - \alpha_q\tilde{q}_t + \rho_u i_{t-1} - \rho_f\tilde{i}_{t-1} + \eta_t \quad , \qquad (4.6)$$

where u and f are subscripts for the domestic and foreign country, and "~" denotes foreign variables. Further, α represents a constant, and for both countries we have that: $\alpha_\pi = \lambda(1-\rho)$ and $\alpha_y = \gamma(1-\rho)$. While for the foreign country we also have $\alpha_q = \delta(1-\rho)$. The error term is now defined as η_t.

Furthermore, a relationship between the interest rate differential and the exchange rate forecast need to be established. Theoretically, one could base this relationship on UIRP, however empirical evidence suggests that UIRP does not hold in the short run. In order to develop the link between the interest rate differential and the exchange rate equation, Molodtsova and Papell (2009) establish several predictions. If an event triggers the raise of the federal funds rate, a theoretical perspective would imply immediate dollar appreciation, followed by forecasted depreciation. Hence, if UIRP holds, a forecasting equation could be developed by replacing the interest rate differential with the expected rate of depreciation, using the Taylor rule for two countries to forecast the exchange rate (Molodtsova and Papell, 2009). However, empirical evidence and the work of Gourinchas and Tornell (2004) argues that a raise in the federal funds rate will lead to immediate dollar appreciation, followed by forecasted appreciation. Based on this argumentation, we reverse the signs of the coefficients in equation (4.6), and develop the following equation for the exchange rate prediction:

$$\Delta s_{t+1} = \omega - \omega_{u\pi}\pi_t + \omega_{f\pi}\tilde{\pi}_t - \omega_{uy}y_t + \omega_{fy}\tilde{y}_t + \omega_q\tilde{q}_t - \omega_{ui}i_{t-1} + \omega_{fi}\tilde{\imath}_{t-1} + \eta_t \ , \qquad (4.7)$$

where the variable s_t is the log of the domestic currency's nominal exchange rate. The exchange rate is determined as the domestic price of foreign currency. q_t is the real exchange rate, π_t represents the inflation rate, y_t is the output gap, while u and f are subscript for the domestic and foreign country, and "~" denotes foreign variables. ω is now the constant, that denoted α in equation (4.6), and ω´s with subscripts are coefficients.

There are a number of possibilities when it comes to the right hand side of equation (4.7). We wish to follow in line with Molodtsova and Papell (2009), and therefore consider four different specifications:

1. Symmetric vs. Asymmetric. If the central bank does not target the exchange rate, we call the equation symmetric. The symmetric model is based on Taylor's (1993) original specification, and does not include the real exchange rate on the right hand side ($\omega_q = 0$). The asymmetric model on the other hand includes the real exchange rate. Following CGG (1998) it is common practice when it comes to other countries than the US, to include the real exchange rate in the monetary policy rule. For this reason, Molodtsova and Papell (2009) postulate that the foreign bank includes the difference between the exchange rate and the target exchange rate, defined by PPP in its Taylor rule.

2. Smoothing vs. no smoothing. The model with no smoothing is developed when the lagged interest rate differential is not included on the right hand side ($\omega_{fi} = \omega_{ui} = 0$). If the interest rate only partially adjusts to the target within the period, we construct a model with smoothing, so that the lagged interest rate differential appears on the right hand side.

3. Heterogeneous vs. homogeneous. Assuming that the Norwegian central bank and the Federal Reserve (FED) respond identically to changes in inflation and output gap and also their interest smoothing coefficients are equal, we have a homogeneous model. Here the coefficients in their Taylor rules are equal, and the relative (domestic minus foreign) inflation, the relative output gap, and the lagged interest rate differential is on the left hand side ($\omega_{u\pi} = \omega_{f\pi}$, $\omega_{uy} = \omega_{fy}$, and $\omega_{fi} = \omega_{ui}$). If the central banks do not respond identically, we have a heterogeneous model. In this case the variables will appear separately.

4. Constant vs. no constant. A model with no constant ($\omega = 0$) is derived if the countries, in addition to having the same responds to changes in inflation and output gap, also have identical target inflation rates and equilibrium real interest rates. Otherwise we include a constant term in our model.

4.2 Interest Rate Fundamentals Model

If one assumes that UIRP holds, it can be used as a forecasting equation. However, a more flexible specification is required, since exchange rate movements may consist with UIRP in the long run, but not in the short run. This results in a forecasting equation, depending on the interest rate differential (Clark and West, 2006):

$$\Delta s_{t+1} = \alpha + \beta(i_t - \tilde{\imath}_t) \quad , \qquad (4.8)$$

where the change in domestic currency's nominal exchange rate is a function of the interest rate differential. From this equation we observe possible consistency with UIRP, since we do not restrict β. If $\beta = 1$ with a positive sign, this model would be consistent with the UIRP.

4.3 Benchmark Model

In order to evaluate the forecasting ability of the alternative models we develop, a benchmark model needs to be established. The consensus in the exchange rate literature is to use a random walk with or without drift as a benchmark. The random walk is defined as a time series process that only depends on past values of itself (Bjørnland and Thorsrud, 2015). If the exchange rate follows a random walk, this implies that the best forecast of the exchange rate today is yesterday's exchange rate, namely a Martingale process:

$$\Delta s_{t+1} = 0 \ , \tag{4.9}$$

where Δs_{t+1} represents the change in the exchange rate.

Exchange rate literature argues that a random walk without drift is the toughest benchmark to beat, and should be used as the benchmark model (Rossi, 2013). However, several of the Taylor rule fundamentals models include a constant. Therefore, it is interesting also to examine how the models performs compared to a random walk with drift:

$$\Delta s_{t+1} = \delta_t \ , \tag{4.10}$$

where Δs_{t+1} still represents the change in the exchange rate, however, we have now included a drift term δ_t.

4.4 Out-of-Sample Performance

The predictive ability of the Taylor rule fundamentals can be evaluated according to in-sample fit or out-of-sample forecast performance. In an in-sample test one observes if the lagged predictor has explanatory power over the full sample (Rossi 2013, 1093). Although less popular than out-of-sample forecasting, in-sample tests have been frequently used in the exchange rate literature, like in Anderson et al (2003). Nevertheless, the main preference in the exchange rate literature is using an out-of-sample test. An out-of-sample performance test "assess whether the predictors would have improved the exchange rate predictions in forecasting environments that mimic as closely as possible the one faced by forecasters in practice" (Rossi 2013, 1079). Consequently, the out-of-sample test is closer to reality and therefore a much harder test to beat. For this reason, we choose to look at out-of-sample predictability.

The full sample is divided into an in-sample portion and an out-of-sample portion, and we use a rolling window regression. In rolling window forecasting the parameter is re-estimated over time using the most recent R observations, where R is known as the window size. Rolling window regressions are often used when there is a case of parameter instability or structural change is suspected (Cheung, Chinn and Pascual 2005, 1155). In a rolling window regression the out-of-sample period changes as we change the estimation window size. A larger estimation window size implies that a larger proportion of the sample is used for estimation, and a smaller proportion is used for out-of-sample forecast evaluation. For this reason we change the estimation window size, to check for sensitivity in our results.

4.5 Forecast Evaluation Method

The forecasting ability of the models is measured by a loss function, and the common choice is to use the Root Mean Squared Forecast Error (RMSFE). A model forecasts better than the random walk if the RMSFE of the fundamental model is smaller than the RMSFE of the random walk.

$$RMSFE = \sqrt{\sum E[(s_{t+h} - \hat{s}_{t+h})^2]} = \sqrt{\sum E[(v_{t+h})^2]} \ , \qquad (4.11)$$

Here, s_{t+h} is the exchange rate at time t+h, $\hat{s}_{t+h}$ is the predicted exchange rate, and v_{t+h} is the error term. The forecast precision is measured by the ratio of the RMSFE from the benchmark model and the alternative model. A ratio that is smaller than 1 implies that the alternative model outperforms the random walk.

4.6 Evaluating Forecast Accuracy

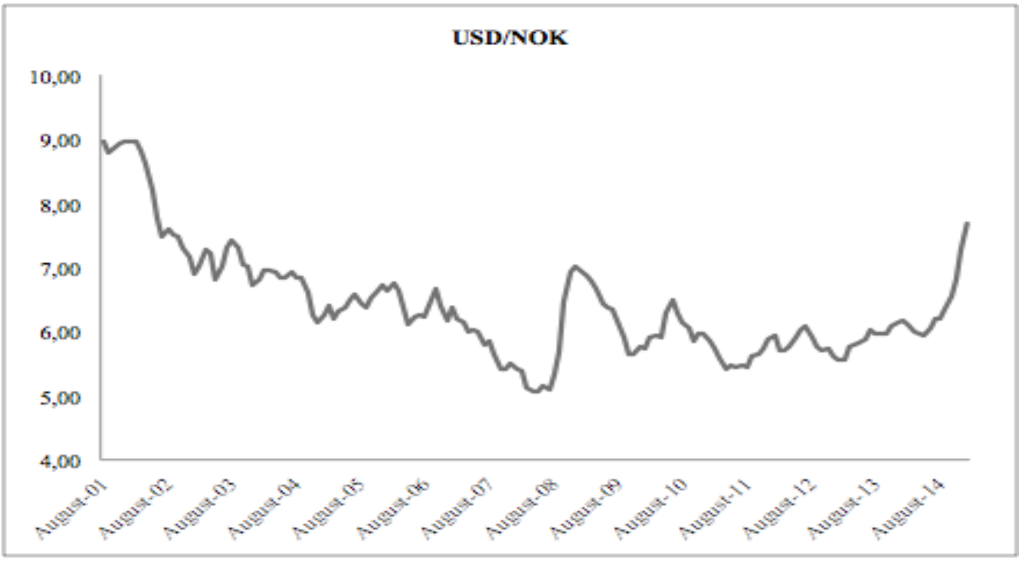
By using RMSFE we evaluate the forecasting ability of our models, however, we would also like to assess the significance of our results. There are several tests that are used in the exchange rate literature to evaluate the forecast accuracy, but we choose to use the test developed by Diebold and Mariano (1995) and West (1996). The DMW-test evaluates whether two competing models have the same forecasting ability. The null hypothesis in our case is that the Mean Squared Forecast Error (MSFE) of the random walk is equal to the MSFE of our alternative model, stating that the forecasts have the same level of accuracy. The alternative hypothesis is that the MSFE of the two models are different, suggesting that the forecasts have different levels of accuracy. One should, however, note that DMW-tests rarely reject the null hypothesis, since it does not take into account that the models are nested. The test does not take into account that one would expect the alternative model to have a higher MSFE than the benchmark model. Hence, the DMW-test, requires a high level of significance before it rejects the models, and is therefore a harder test to beat than comparable tests.

5. Data

The models in our study will be estimated using monthly data from August 2001 to February 2015. In the exchange rate literature both monthly and quarterly data has been used, however, the frequency of data does not seem to have significant implications for the results (Rossi, 2013). Considering the size of our sample, using monthly data is beneficial, since it provides us with a larger number of observations.

Norway introduced inflation targeting in 2001, and this is the natural starting point for our analysis. Data collection after February 2015 can be challenging, therefore we limit our sample to this date. Even though we limit the sample to February 2015, we are under the impression that we have enough monthly data points to make a satisfying analysis.

The currencies to be considered in the analysis are US Dollars and Norwegian Krone. In order to construct the models, data on output gap, inflation, interest rates and exchange rates are required. Data on Consumer Price Index (CPI), exchange rates and interest rates are publically available from the Norwegian Central Bank and the Federal Reserve Bank of St. Louis. CPI measures the price level in the economy, and we use the 12-months difference of the CPI as the inflation rate. When it comes to the exchange rate, we need to consider whether to look at monthly averages or a particular date in the month. In our analysis the exchange rate data is from the 15th of each month.



Graph 5.1. Notes: Presents the development of the USD/NOK exchange rate from 2001M08 to 2015M02.

Graph 5.1 presents the exchange rate movements from 2001M08-2015M02. After Norway changed their monetary policy regime, and introduced inflation targeting in 2001, large exchange rate fluctuations have been observed. The high exchange rate in 2001 reflects the economic growth in the United States during the Dot-com Bubble. After the Bubble the US dollar depreciated, reaching an all-time low at the beginning of the financial crisis in late 2007.

The global financial crisis during 2007-2009 generated rare exchange rate movements. The NOK sharply depreciated against the US dollar in August 2008, before appreciating during the next year. Commodity-exporting countries such as Norway recovered earlier than other economies, due to renewed strength in commodity prices and high interest rates (Kohler, 2010). This phenomenon of depreciation against the US dollar was also observed for other currencies that were not in the centre of the crisis. However, the fast appreciation of the NOK was rare.

The US central bank uses the Fed-funds rate as a monetary policy instrument, which is a short-term interest rate. The Norwegian central bank uses the Norwegian key rate, which is an over-night short-term interest rate. To make the two measurements comparable on short-term, we use the Norwegian Interbank Offered Rate (NIBOR) as a measure for the Norwegian interest rate. For the US we use the Fed-Funds rate.

The output gap is challenging to define, therefore, several alternatives need to be taken under consideration. The gap depends on the measure of potential output, and there is no presumption about which definition of potential output the central banks use in their reaction functions. GDP is often used as a measure of the output gap, but using GDP has its disadvantages. First of all, GDP is available only on quarterly terms, while we consider monthly data. Secondly, GDP is subjected to data revisions, and this does not correspond with our intention to use real time data.

One frequently used proxy for the output gap is the Industrial Production Index, and this will be our measure of national income. We consider percentage deviations from a linear trend and also include a Hodrick Prescott (HP) trend as an alternative measure of the output gap. As we follow in line with Molodtsova and Papell (2009), we use a smoothing parameter equal to $\lambda = 14\,400$ when detrending the monthly output series.

6. Empirical Results

We construct one-month-ahead forecasts with each of the specifications presented in chapter four. The specifications provide us with 16 different models to construct. Since we also include two different measures of the output gap, both a linear trend and a HP-filter, we have 32 models in total. The time period for estimation is 2001M08-2005M06, and the remaining part of the sample is used for forecasting. The models are estimated with the 48 first data points, and a one-month-ahead forecast is developed. The parameters are then re-estimated over time using the most recent 48 observations. Further, the parameters are used to predict the exchange rate, and we compare the predicted rate with the realised one to construct the RMSFE. Finally, we use relative RMSFE to compare the performance of the Taylor rule fundamentals model and our benchmark model the random walk.

6.1 Choice of Benchmark Model and Performance of UIRP

First of all, we examine which model that should be used as our benchmark model, and then evaluate the performance of the interest rate fundamental model.

Table 6.1 presents the RMSFE of a random walk with and without drift, where the RMSFE is observed to be lowest for the latter. The random walk without drift is therefore the hardest benchmark to beat, and consequently will be used as our benchmark model.

	Random walk
Without drift	0,02724
With drift	0,02824

Table 6.1. Notes: This table reports RMSFE for a random walk with and without drift.

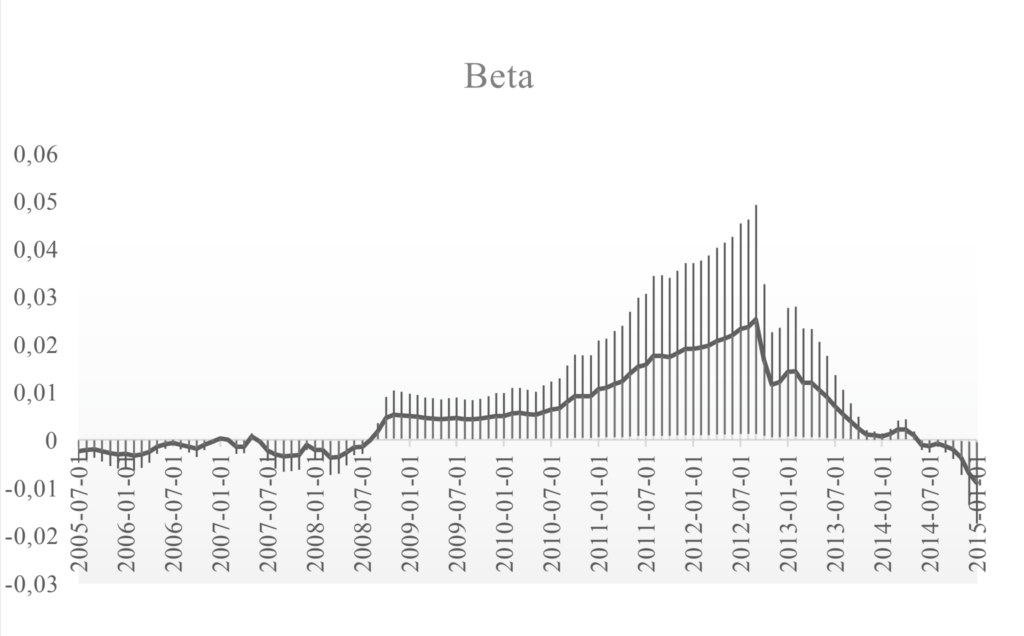
The Meese and Rogoff puzzle suggests that a random walk will be able to forecast better than the UIRP. This surprising finding contradicts economic theory, which argue that the UIRP should be the best forecasting predictor. However, our finding corresponds to that of Meese and Rogoff (1983). Table 6.2 below presents the forecasting performance of the interest rate fundamental model and the traditional UIRP. The table displays the relative RMSFE, and we observe that none of the models outperform the random walk. The random walk outperforms the interest rate fundamental model both with and without a constant. This result is consistent with the findings of Meese and Rogoff (1983), but in contrast to studies like Cheung, Chinn and Pascual (2005) and Alquist and Chinn (2008) who find support for UIRP for some countries.

	Interest rate fundamentals model	**UIRP**
Without drift	1,0501	99,1695***
With drift	1,0491	-

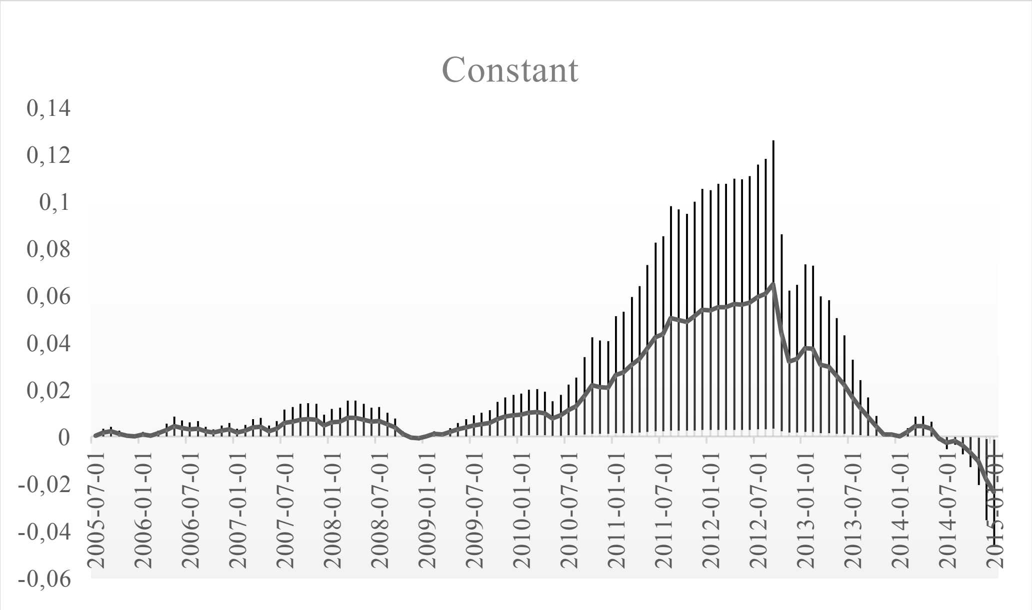
Table 6.2 Notes: The table reports relative RMSFE values for 1-month-ahead forecasts between a random walk and the alternative model. In this table the alternative model is an interest rate fundamentals model with and without drift, presented in equation (4.8), and UIRP with $\alpha = 0$ and $\beta = 1$. The window size is set to 48, and "***" indicate a significance level of 1 %.

Table 6.2 also displays the traditional UIRP with no constant ($\alpha = 0$) and intercept equal to one ($\beta = 1$). The traditional UIRP turns out to have lower forecasting ability than the random walk, at 1 % significance level. The traditional UIRP implies that the interest rate differential is equivalent to the change in the exchange rate in the same period. However, the empirical evidence does not support UIRP. Studies like Chen and Tsang (2013) find that the coefficient β is not equal to one, and the constant α is not equal to zero, hence the UIRP condition is violated. The finding in table 6.2, that the relative RMSFE-value of UIRP is 99.1695, illustrates how poor UIRP is when it comes to forecasting ability. There exist numerous explanations to why the UIRP fails, however the main explanation relates to the presence of time-varying risk premiums and expectation errors (Chen and Tsang, 2013). The finding of Chen and Tsang (2013) is consistent with our findings, UIRP does not hold.

Graph 6.1 stipulates the development of Beta from the period of 2005M07, to 2015M01. As observed it is not equal to one, and has a mean of 0,0049. The development of the constant is presented in graph 6.2, and show that the constant is different from zero with a mean of 0,0144.



Graph 6.1. Notes: Displays the development of the intercept in the period from 2005M07-2015M02, where the shaded area is the 95% confidence interval.



Graph 6.2. Notes: Displays the development of the constant in the period from 2005M07-2015M02, where the shaded area is the 95% confidence interval.

The shaded areas in graph 6.1 and 6.2 are the respective confidence intervals. The 95% confidence interval in the two graphs is observed to be wider from around 2009 till 2013. The reason for this larger variation can be connected to the financial crisis. During this period after the financial crisis the exchange rate may have fluctuated more than earlier. Consequently, the variation in exchange rates in this period may not be explained by changes in interest rates in the same way as before. Therefore, for the UIRP to hold, the variation is instead expressed through the constant and the intercept, leading to wider variation.

6.2 Taylor Rule Fundamentals Model

With the different specifications taken into account, and considering both a linear trend and a HP-filter as the measure of the output gap, it is evident that the models that are estimated with a linear trend and heterogeneous coefficients produce the best performing results. In fact, looking at table 6.3 below, it is clear that model 1, 3, 4 and 8 have a higher forecasting ability than the random walk, when output gap is determined by a linear trend and the coefficients are heterogeneous. The best performing model is model 1. This model is based on heterogeneous coefficient and it includes the real exchange rate, the lagged interest rate, and a constant. The DMW-test suggests that none of these models significantly outperforms a random walk. Nevertheless, we find the results encouraging, since performing this test on nested model leads to too few rejections of the null hypothesis. Further, we also find the results promising, since the numbers of relative RMSFE are equivalent to numbers in other comparable studies where they find significance (Molodtsova and Papell, 2012).

	Heterogeneous			Homogeneous		
	Relative RMSFE	*DMW-statistic*	*P-value*	*Relative RMSFE*	*DMW-statistic*	*P-value*
Linear trend						
(1) Asymmetric, smoothing, constant	0,9586	0,5287	0,5980	1,0994	-0,6780	0,4991
(2) Asymmetric, no smoothing, constant	1,0180	0,1412	0,8880	1,1905**	-2,6007	0,0105
(3) Asymmetric, no smoothing, no constant	0,9680	0,7651	0,4458	1,1177*	-1,9661	0,0517
(4) Asymmetric, smoothing, no constant	0,9778	0,3796	0,7049	1,1221*	-1,6975	0,0923
(5) Symmetric, no smoothing, constant	1,0056	0,3085	0,7583	1,1101*	-1,8014	0,0743
(6) Symmetric, smoothing, no constant	1,1203	-1,5309	0,1286	1,1215	-1,1612	0,2480
(7) Symmetric, smoothing, constant	1,0484	-0,1902	0,8495	1,0868	-0,8510	0,3966
(8) Symmetric, no smoothing, no constant	0,9899	0,5626	0,5748	1,0830	-1,2205	0,2248
HP-filter						
(1) Asymmetric, smoothing, constant	0,9832	0,3403	0,7342	1,1703	-1,1350	0,2588
(2) Asymmetric, no smoothing, constant	1,1359	-0,9510	0,3436	1,2117*	-1,9682	0,0515
(3) Asymmetric, no smoothing, no constant	1,0898	-0,6582	0,5118	1,1079	-1,4631	0,1462
(4) Asymmetric, smoothing, no constant	1,0714	0,4085	0,6837	1,0977	-0,9750	0,3316
(5) Symmetric, no smoothing, constant	1,0887	0,8955	0,3724	1,0992	-1,3804	0,1702
(6) Symmetric, smoothing, no constant	1,0764	0,5855	0,5594	1,8604***	-5,7533	0,0000
(7) Symmetric, smoothing, constant	1,0898	0,6785	0,4989	1,0697	-0,4369	0,6630
(8) Symmetric, no smoothing, no constant	0,9880	0,5933	0,5541	1,0809	1,1475	0,2536

Table 6.3. Notes: This table reports relative RMSFE values for 1-month a head forecast between a random walk and the alternative model, which is a linear model with Taylor rule fundamentals. A relative RMSFE value below 1 indicates that the alternative model outperforms the random walk. The table also reports the DMW-statistic and the corresponding p-value, where "*", "**", "***" indicate the 10, 5, and 1 % significance level. The table reports the values for a rolling window of R=48, and the full sample is used.

From table 6.3 we observe that models constructed with the HP-filter as the measure of output gap, perform worse than models constructed with a linear trend. In our study our intention is to use real-time data, that is information that was available to all market participants at time t. However, when constructing the HP-filter we use the whole sample to identify the trend and the business cycles. This violates the real-time data criteria, since this future information on the output gap was not available to the central banks at the time they set their interest rate. In Molodtsova and Papell (2009), they use quasi real-time data, and for this reason they have been criticized by other scholars (Orphanides, 2001). The critics argue that when the real-time data condition is violated, one can not conclude with superior out-of-sample forecasting ability of the models. Because of our construction of the HP-filter, the same accounts for our study. However, it is interesting that the models constructed with this filter do not perform better than the ones constructed with a linear trend.

6.3 Sensitivity Analysis

After studying former exchange rate literature, it is clear that the choice of the benchmark, horizon, sample period, and forecast evaluation methods will have an impact on the results. In this section we wish to evaluate how sensitive our results are to changes in the sample, and the size of rolling window.

6.3.1 Rolling Window Sensitivity

Rossi (2013) argues that the window size strongly affects predictability for some countries. Until now, we have used a window size of 48, that is four years. In table 6.4 and 6.5 we investigate what happens if we were to reduce the window size to 24, and to increase it to 80.

	Heterogeneous			Homogeneous		
	Relative RMSFE	*DMW-statistic*	*P-value*	*Relative RMSFE*	*DMW-statistic*	*P-value*
Linear trend						
(1) Asymmetric, smoothing, constant	0,9662	0,2623	0,7935	1,4309***	-3,0235	-3,0235
(2) Asymmetric, no smoothing, constant	1,0549	-0,6917	0,4903	1,1690**	-2,3222	0,0217
(3) Asymmetric, no smoothing, no constant	1,0289	-0,3876	0,6989	1,1085*	-1,9661	0,0513
(4) Asymmetric, smoothing, no constant	0,9612	0,2934	0,7696	1,0822	-1,3063	0,1936
(5) Symmetric, no smoothing, constant	0,9919	0,0329	0,9738	1,1028*	-1,9134	0,0578
(6) Symmetric, smoothing, no constant	1,0750	-1,1740	0,2424	1,3470***	-3,6950	0,0003
(7) Symmetric, smoothing, constant	1,0185	-0,2639	0,7923	1,3899***	-3,0044	0,0032
(8) Symmetric, no smoothing, no constant	1,0238	-0,3779	0,7061	1,0656	-1,2842	0,2012
HP-filter						
(1) Asymmetric, smoothing, constant	0,9336	0,1764	0,8602	1,1475***	3,0635	0,0026
(2) Asymmetric, no smoothing, constant	1,0049	1,0933	0,3762	1,1364**	-2,0629	0,0410
(3) Asymmetric, no smoothing, no constant	0,9614	-1,5413	0,1256	1,1010**	-2,4752	0,0145
(4) Asymmetric, smoothing, no constant	0,9284	-0,3345	0,7385	1,1025*	-1,8560	0,0656
(5) Symmetric, no smoothing, constant	0,9953	1,2842	0,2012	1,1007**	2,0460	0,0427
(6) Symmetric, smoothing, no constant	1,0454	0,9624	0,3375	1,0870***	-7,3501	0,0000
(7) Symmetric, smoothing, constant	1,0151	0,8751	0,3830	1,0846***	-2,6616	0,0087
(8) Symmetric, no smoothing, no constant	0,9656	-1,1765	0,2414	1,1049**	-2,0299	0,0443

Table 6.4. Notes: This table reports relative RMSFE values for 1-month a head forecast between a random walk and the alternative model, which is a linear model with Taylor rule fundamentals. A relative RMSFE value below 1 indicates that the alternative model outperforms the random walk. The table also reports the DMW-statistic and the corresponding p-values, where "*", "**", "***" indicate the 10, 5 and 1 % significance level. The table reports the values when a rolling window with R= 24 is considered, and the full sample is being used.

Table 6.4 presents the results when we consider a window size of 24. The period from 2001M08-2003M08 is used for estimation, and the remaining part of the sample 2003M09-2015M02, is used as the forecast evaluation period. After performing the adjustment, the models that are estimated with HP-filter generally perform better than the ones estimated with a linear trend. None of these models can be defined as statistically significant after conducting the DMW-test. However, this result may be due to the fact that the DMW-test rarely rejects the null-hypothesis. The best performing model with this rolling window is estimated using HP-filter, and is an asymmetric model, with interest rate smoothing and no constant (model 4).

	Heterogeneous			Homogeneous		
	Relative RMSFE	*DMW-statistic*	*P-value*	*Relative RMSFE*	*DMW-statistic*	*P-value*
Linear trend						
(1) Asymmetric, smoothing, constant	0,9748	1,2848	0,2025	1,6447	-1,3651	0,176
(2) Asymmetric, no smoothing, constant	1,1044	0,7411	0,4608	1,2167	-1,3278	0,1879
(3) Asymmetric, no smoothing, no constant	1,1626	1,3385	0,1845	1,1548	-1,6343	0,106
(4) Asymmetric, smoothing, no constant	1,0323	1,3509	0,1804	1,1280	-1,6007	0,1133
(5) Symmetric, no smoothing, constant	1,0892	1,1972	0,2347	1,1242*	-1,7210	0,089
(6) Symmetric, smoothing, no constant	1,0659	0,5783	0,5646	2,4588	-0,6806	0,498
(7) Symmetric, smoothing, constant	1,0700	0,8196	0,4148	1,5588	-0,6397	0,5241
(8) Symmetric, no smoothing, no constant	1,0893*	1,6743	0,0979	1,1034***	-2,7119	0,0081
HP-filter						
(1) Asymmetric, smoothing, constant	1,0186	-0,2993	0,7655	1,2058*	-1,8854	0,0630
(2) Asymmetric, no smoothing, constant	1,0829	0,2343	0,8153	1,1728	-1,5931	0,1150
(3) Asymmetric, no smoothing, no constant	1,0543	0,2723	0,7861	1,1115	-1,0135	0,3138
(4) Asymmetric, smoothing, no constant	1,0467	0,1900	0,8498	1,1217	-1,3233	0,1894
(5) Symmetric, no smoothing, constant	1,0487	-0,3517	0,7260	1,1170	-1,2172	0,2270
(6) Symmetric, smoothing, no constant	1,0670	-0,0390	0,9690	1,5747***	5,5800	0,0000
(7) Symmetric, smoothing, constant	1,1291	0,7255	0,4702	1,1400	-1,6338	0,1062
(8) Symmetric, no smoothing, no constant	1,0508	0,3416	0,7335	1,1469***	-2,7491	0,0073

Table 6.5. Notes: This table reports relative RMSFE values for 1-month a head forecast between a random walk and the alternative model, which is a linear model with Taylor rule fundamentals. A relative RMSFE value below 1 indicates that the alternative model outperforms the random walk. The table also reports the DMW-statistic and the corresponding p-value, where ”*”, “**”, “***” indicate the 10, 5 and 1 % significance level. The table above reports the respective values using a rolling window of R=80, and the sample is set to 2001M08-2015M02.

Table 6.5 above reports the results when a window size of 80 is considered. The estimation period is 2001M08-2008M04, and the forecast evaluation period is 2008M05-2015M02. After this adjustment, we observe that there is only one model that outperforms the random walk. Once again this is the model including a linear trend, heterogeneous coefficients, interest rate smoothing and a constant (model 1). This is the model that we defined as the best performing also with R=48, and we observe that it outperforms the random walk with both window size set to R=24, and R=80. Hence, model 1 estimated using linear trend, performs better than the random walk, independently of the choice of R.

In table 6.5 we observe that all the models perform relatively weaker when we introduce a longer rolling window. This finding is not surprising, because we use the period before the financial crisis for estimation, and the period during and after the financial crisis as our forecast evaluation period. It is challenging to foresee a crisis before it actually happens, and hence hard to predict. The finding that the models now have a weaker performance, may be a consequence of using a large window size. The first data in the evaluation period may then have little predictive power for the forecast evaluation, because of the large time span between the used data point, and the forecasted data point. However, a large window size also has positive consequences, because we reduce the effect of outliers.

6.3.2 Adjustment of Sample Period

Generally, it is believed that Taylor rules provide a decent description of monetary policy in the last few decades. However, Molodtsova and Papell (2012) discuss that monetary policy may have altered during and after the financial crisis (Rossi, 2013). The financial crises lasted from 2008 to 2009, where the peak of the crisis was in the last quarter of 2008 (Molodtsova and Papell, 2010). Several studies have found that the financial crisis impact exchange rate predictability, and therefore we find it interesting to change our sample. We test if our models can outperform the random walk before, and after the financial crisis. Firstly, we change our sample from 2001M08 to 2007M12, and the results are presented in table 6.6 below.

	Heterogeneous			Homogeneous		
	Relative RMSFE	*DMW-statistic*	*P-value*	*Relative RMSFE*	*DMW-statistic*	*P-value*
Linear Trend						
(1) Asymmetric, smoothing, constant	0,9669	0,2312	0,8188	1,1582	-1,6527	0,1100
(2) Asymmetric, no smoothing, constant	1,1064	-1,1838	0,2464	1,2051**	-2,2724	0,0309
(3) Asymmetric, no smoothing, no constant	1,1424	-1,4940	0,1468	1,1087**	-2,5173	0,0178
(4) Asymmetric, smoothing, no constant	0,9692	0,2147	0,8315	1,1031**	-2,6041	0,0146
(5) Symmetric, no smoothing, constant	1,0107	-0,1912	0,8498	1,0844**	-2,4225	0,0221
(6) Symmetric, smoothing, no constant	1,1375	-1,3589	0,1850	0,9638	1,2923	0,2068
(7) Symmetric, smoothing, constant	1,0598	-0,5942	0,5571	1,0671	-1,5095	0,1428
(8) Symmetric, no smoothing, no constant	1,1445**	-2,3335	0,0273	0,9808	0,7592	0,4540
HP-filter						
(1) Asymmetric, smoothing, constant	1,0976	-0,5497	0,5869	1,1434	-1,0282	0,313
(2) Asymmetric, no smoothing, constant	1,2510	-1,5615	0,1296	1,1869	-1,4576	0,1561
(3) Asymmetric, no smoothing, no constant	1,2410	-1,5224	0,1395	1,1999	-0,4873	0,6298
(4) Asymmetric, smoothing, no constant	1,1668	-0,9555	0,3475	1,0826	-0,8834	0,3846
(5) Symmetric, no smoothing, constant	1,1372	-1,0655	0,2957	1,0064	-0,1220	0,9037
(6) Symmetric, smoothing, no constant	1,1653	-1,2707	0,2143	0,9766	0,4413	0,6624
(7) Symmetric, smoothing, constant	1,1523	-1,1867	0,2453	0,9984	0,1667	0,8688
(8) Symmetric, no smoothing, no constant	1,0563	-0,7221	0,4765	0,9607	0,8672	0,6298

Table 6.6. Notes: This table reports relative RMSFE values for 1-month a head forecast between a random walk and the alternative model, which is a linear model with Taylor rule fundamentals. A relative RMSFE value below 1 indicates that the alternative model outperforms the random walk. The table also reports the DMW-statistic and the corresponding p-value, where “*”,”**”, ”***” indicate the 10, 5 and 1 % significance level. The table above reports the values when a rolling window of R=48 is considered, and our sample runs from August 2001 to December 2007.

From table 6.6 we observe that after the sample adjustment, model 1 still outperforms the random walk. Moreover, three models estimated with linear trend, and three models estimated with HP-filter outperform the random walk.

The period after the financial crisis is also examined, and the results are presented in table 6.7 below. The sample period is from 2009M06 to 2015M02. This provides us with a smaller sample, and using a rolling window of four years, there is few data points left to forecast. This might bias the results. In table 6.7 we can observe that as much as 28 out of 32 models outperform the random walk, however not significantly.

	Heterogeneous			**Homogeneous**		
	Relative RMSFE	*DMW-statistic*	*P-value*	*Relative RMSFE*	*DMW-statistic*	*P-value*
Linear Trend						
(1) Asymmetric, smoothing, constant	0,9455	0,3500	0,7300	0,7201	1,6440	0,1166
(2) Asymmetric, no smoothing, constant	1,0049	0,1837	0,8561	0,9292	0,4767	0,6388
(3) Asymmetric, no smoothing, no constant	0,7170	1,5716	0,1326	0,9525	1,4359	0,1665
(4) Asymmetric, smoothing, no constant	0,9357	0,3769	0,7102	0,9573	1,3661	0,1871
(5) Symmetric, no smoothing, constant	0,8971	1,3530	0,1911	0,9488	1,4801	0,1544
(6) Symmetric, smoothing, no constant	0,9848	0,6797	0,6797	0,8273*	1,7947	0,0878
(7) Symmetric, smoothing, constant	0,8653	0,9554	0,3508	0,9294	1,3803	0,1835
(8) Symmetric, no smoothing, no constant	0,9400*	2,0509	0,0543	0,9286	1,5710	0,1319
HP-filter						
(1) Asymmetric, smoothing, constant	0,8636	0,6351	0,5326	0,6383*	1,9192	0,0701
(2) Asymmetric, no smoothing, constant	1,0180	0,1460	0,8854	0,9466	0,3797	0,7081
(3) Asymmetric, no smoothing, no constant	0,8779	1,2730	0,2184	0,8636	1,2886	0,2123
(4) Asymmetric, smoothing, no constant	0,8092	0,8383	0,4117	0,8707	1,0611	0,3013
(5) Symmetric, no smoothing, constant	0,9710	0,5892	0,5623	0,8755	1,4746	0,1559
(6) Symmetric, smoothing, no constant	0,9417	0,5304	0,6017	2,8963***	-3,8702	0,001
(7) Symmetric, smoothing, constant	0,9832	0,4308	0,6712	0,6905**	2,1002	0,0493
(8) Symmetric, no smoothing, no constant	0,8743*	1,8715	0,0768	1,0514	0,1905	0,8508

Table 6.7. Notes: This table reports relative RMSFE values for 1-month a head forecast between the null of a random walk and the alternative model, which is a linear model with Taylor rule Fundamentals. A value that is lower than 1, indicates that the alternative model outperforms the random walk. The table also reports the DMW-statistic and the corresponding p-value, where “*”, “**”, “***” indicate the 10, 5 and 1 % significance level. The table above reports the values when a rolling window of R=48 is considered, and the sample runs from 2009M06-2015M02.

The results presented in this chapter indicate that the performances of our models are very sensitive to changes in the sample period and the rolling window. However, despite these changes, some of the models seem to have higher predictive ability than the random walk. The model that provide us with the best performance, is the heterogeneous, asymmetric model, with smoothing, a constant, and with output gap measured as deviations from a linear trend (model 1).

7. Discussion

This master thesis is based on the work of Molodtsova and Papell (2009). In their paper they examine out-of-sample predictability using Taylor rule fundamentals. They subtract the Taylor rule for the foreign country from the Taylor rule for the domestic country, taking a number of different specifications into account. The interest rate differential is on the left-hand-side, while there are several possibilities on the right-hand-side. Molodtsova and Papell (2009) find very strong evidence of exchange rate predictability with Taylor rule fundamentals on 11 out of 12 countries, relative to the USD. Their strongest evidence is found for the Taylor rule model that is symmetric, heterogeneous, with smoothing, and with a constant.

The analysis we perform is conducted using the same models as presented by Molodtsova and Papell (2009), using the USD/NOK exchange rate. The model that turns out to perform the best is an asymmetric Taylor rule model with a constant, interest rate smoothing and heterogeneous coefficients. The difference between our and Molodtsova and Papell's (2009) best performing model, is that we include the real exchange rate of the foreign currency so that it becomes asymmetric. It is important to emphasise that these results may not coincide, because the two studies are conducted on different currencies to the US dollar, and that the data series are from different time epochs.

The best performing model in our research is specified with heterogeneous coefficients and includes a constant. A heterogeneous model takes into account that the central banks do not respond identically to changes in inflation and the output gap, and subsequently, the coefficients are not the same. If we were to not include a constant it would suggest that the Norwegian Central Bank and the FED would have the same inflation targets and equilibrium interest rates. The target inflation rate in Norway is 2.5 percent over time, while in the US it is 2 percent. Subsequently, this is definitely not the case, and this supports the use of the model that includes a constant and heterogeneous coefficients.

Monetary policy may have changed during the global financial crisis in 2007, and even though Taylor rules are considered to be a good description up until the financial crisis, this may have been altered during and after the crisis. In our sample we consider a time where the economic environment was pressured, and the federals funds rate was at the zero lower bound. The federal funds rate hit the zero lower bound in late 2008, and in this period Taylor rule for monetary policy went from being descriptive to prescriptive (Molodtsova and Papell, 2012, 23).

In their recent paper, Molodtsova and Papell (2012) investigate the USD/EUR exchange rate, and found that prior to the financial crisis models using interest rate fundamentals performs equally as good as Taylor rule fundamentals. However, once the financial crisis hit, the FED and the European central bank lowered their interest rates, and following, Taylor rule models once again outperformed the models with interest rate as their fundamental. In our case we study the whole sample period, as well as the period before and after the financial crisis. When we apply the whole sample and a rolling window of 80, this leads to an estimation of the coefficients before the crisis, and a forecast evaluation period during and after the crisis. Not surprisingly, estimating the coefficients in this way provides us with our weakest results. However, it is challenging to make further inference about the relative performance of our models before and after the financial crisis. We observe that the performance of the models improve when only examining the period after 2009M06. However, eliminating such a large part of the sample leaves us with very little data to evaluate the forecast.

The choice of data in our analysis is obviously critical for the results. The most suitable data for out-of-sample forecasting is real-time data, that is data that was available for market participants at the time. The use of real-time data is important when applying Taylor rule estimation, because it reflects the information that was available for central banks when they set the interest rate (Molodtsova and Papell, 2009). Molodtsova and Papell (2009) have been criticised by other scholars because they do not use real-time data. The argumentation is that without real-time data, the results can not be interpreted as successful out-of-sample forecasting (Molodtsova and Papell, 2010). However, because of limited access, and as we follow in line of Molodtsova and Papell (2009), the best comparable replacement of real-time data is quasi-real-time data, and this is what we use in our analysis. The most obvious deviation from real-time data in our analysis is our application of the HP-filter. To construct the output gap, we use the HP-filter to develop the trend and the business cycle. However, constructing the trend using the whole sample implies that we have used information that was not available for the market participants at the time.

The results presented in the previous chapter indicate that none of the Taylor rule models that outperform the random walk are significant. The only results that turn out to be significant are those where the random walk outperforms the Taylor rule fundamentals model. One reason for the lack of significance in our Taylor rule fundamentals model might be the choice of the forecast evaluation method. The standard in the literature is to use either the Clark and West (CW-test), or the Diebold, Mariano and West test (DMW-test). While Clark and West (2006) test out-of-sample whether the benchmark model is equivalent to the competing model in population, Diebold and Mariano (1995) and West (1996) test whether the competing models forecast ability is the same. In our study we apply the DMW-test.

Recent studies indicate that this forecast evaluation method might not be suitable for models that are nested (Molodtsova and Papell, 2009, 168). Using a DMW-test on models that are nested might lead to too few rejections of the null. The DMW-test is strict, and requires a high significance before rejecting the null-hypothesis. Compared to the random walk, the Taylor rule fundamental models include a higher number of estimated coefficients; therefore, one should expect a higher frequency of error. If we had applied the CW-statistic, it would have taken into account that the RMSFE of the alternative model is expected to be lower than the RMSFE of the fundamental, when the models are nested. Consequently, changing our forecast evaluation method to the CW-statistics could have led to significant results. However, applying the CW-test is usually used when one is interested in evaluating models in populations, while the DMW-test is usually used when one is interested in evaluating forecasts (Rossi, 2013). Since we are interested in the latter, the choice of applying the DMW-test can be justified.

8. Conclusion

In this paper we have examined if Taylor rule fundamentals can predict the USD/NOK exchange rate. On the basis of the Taylor rule, we have constructed 32 models and compared their forecasting ability to the random walk. The model that has the best performance is the asymmetric model with interest rate smoothing, heterogeneous coefficients and a constant. However, after conducting the DMW-test, we find that the performance of this model is not significant. Nevertheless we find our results encouraging, as the DMW-test can lead to too few rejections of the null when the models are nested. Furthermore, we conclude that the performance of our models is very sensitive to changes in the sample period and rolling window.

This paper examines the predictability of the USD/NOK exchange rate. It would also be interesting to evaluate the forecasting performance of other currency pairs. Therefore, we would encourage other studies to examine the predictability of other currencies compared to the Norwegian Krone. In this study we lack significance for our Taylor rule fundamental models. The lack in significance may be due to our forecast evaluation method. Therefore, it would be interesting for other scholars to change the forecast evaluation method, as this might alter the results.

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