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Testing Exchange Rate Models in a Small Open Economy: an SVR Approach

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Abstract

We empirically test the validity of four popular monetary exchange rate models under five alternative inflation expectation approximations using the NOK/USD exchange rate. The selection of Norway seems appropriate as it is a small open economy that does not participate in most economic or political organizations and uses the Government Pension Fund as a tool to dampen external shocks to the domestic economy. The main innovation of the paper is that in addition to a standard VECM model used in the literature, we employ a two-step procedure for the first time in this setting; first, we train a Support Vector Regression (SVR) model and then we extract the coefficients through a Dynamic Evolving Neural Fuzzy Inference System (DENFIS). The best overall model in terms of fitting the phenomenon is an SVR one with autoregressive inflation expectations that exclude energy prices, exhibiting four times lower forecasting error than the best VECM model. The estimated coefficients of the VECM are not statistically significant, while the ones from the SVR-DENFIS model show that the sign of the coefficient on the interest rate differential corroborates only with the model proposed by Bilson (1978), while we detect a significant inflation rate differential. We conclude that fundamentals possess adequate forecasting ability when used in exchange rate forecasting but none of the tested monetary exchange rate models can explicitly describe the evolution path of the exchange rate. Nevertheless, the proposed machine learning methodology moves one step further than the econometric approach in tackling the exchange rate disconnect puzzle.

JEL classification numbers: G15, F30, F31
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1 Introduction

The reported causal relationship between the exchange rate evolution and monetary policy (Rime *et al*, 2010) led to the introduction of a significant number of monetary exchange

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rate models in order to describe exchange rate dynamics and empirically establish the implied link in the short-run. Building on the seminal work of Meese and Rogoff (1983), Cheung *et al.* (2005) test a broad number of monetary exchange rate models using Error Correction and Rolling Regression techniques. With various exchange rates, they conclude that there is no universal model that spatiotemporally outperforms all the others. This result, is known as the “exchange rate disconnect puzzle” (Obstfeld and Rogoff, 2000) in international economics; i.e., the inability of fundamentals to adequately describe the evolution of the exchange rates, especially in the short-run[2]. Mark and Sul (2001) argue that the univariate models used in Messe and Rogoff (1983) cannot fully capture the underlying data generating process of the exchange rates and thus develop panel data models that exhibit a higher forecasting accuracy. Nevertheless, their results vary across different currencies and time periods. Overall, there is no consensus in the literature regarding the potential validity of structural monetary exchange rate models.

Norway provides an interesting example to test alternative exchange rate models. It is a developed small open economy that does not participate in most international political and economic organizations. It also fosters constant budget surpluses and a low external debt. Moreover, the sovereign wealth fund, currently known as the Government Pension Fund (GPF) is used by the Norwegian government as a tool to dampen external shocks to the domestic economy. It has a present worth of approximately $889.1 billion or roughly 172% of Norway’s GDP. This fund accumulates the income from oil exports in order to: a) provide funding to future generations when oil revenue is expected to decline from its current peak, and b) absorb the effects of oil price fluctuations on domestic demand. Thus, Norway is expected to be more isolated to exogenous shocks than other developed economies and the Norwegian Krone/U.S. Dollar (NOK/USD) exchange rate may be an excellent case to fit and compare alternative exchange rate models. For the NOK/USD case, Papadamou and Markopoulos (2012) apply Johansen and Juselius (1990) cointegration tests and develop Vector Error Correction Models (VECM) using the monetary exchange rate model of general form suggested by Chinn (2007a), in order to compare four popular monetary exchange rate models. They show that: a) the monetary exchange rate models outperform a Random Walk, and b) almost half of the exchange rate variability can be attributed to oil price fluctuations. Unlike VECMs, SVRs have not been used in evaluating monetary exchange rate models. Nevertheless, a significant drawback of VECMs is the definition of a long-run equilibrium relationship between variables that often cannot be supported by the data. In other words, Papadamou and Markopoulos (2012) develop a VECM model evaluating 11 years of data (197Q1 – 2008Q2) which is a rather small length for observing long-run relationships. If a VAR is to be estimated, then econometric issues arise since in the existence of cointegration OLS estimator are biased. On the other hand, SVR methods can deal with non-stationary time series even in the existence of cointegration since the follow a different path in model optimization.

In this paper, we follow the Papadamou and Markopoulos (2012) approach and we empirically test the validity of four popular exchange rate models for the case of Norway. Our innovation is that in doing so, we employ two alternative methodologies: a)

[2] For more information on exchange rate puzzles see Sarno (2005).

standard VECM approach and b) a Support Vector Regression (SVR) model coupled with the Dynamic Evolving Fuzzy-Inference System (DENFIS) methodology. We use quarterly observations spanning the period from 1997Q1 to 2008Q2 for the U.S. and Norway on the money supply (M2), the Consumer Price Indices, the Gross Domestic Product, the NOK/USD nominal exchange rate, the overnight LIBOR and the Norwegian interbank interest rate, and finally real oil prices. In order to approximate the unobserved inflation expectations included in the aforementioned models we use five alternatives: an AR model, an ARMA model, the AR and ARMA excluding the effect of oil prices on the CPI, and a model based on forward exchange rate contracts. The proposed hybrid methodology captures the underlying data generating mechanism of the exchange rate more accurately than VECMs as the empirical results show that the SVR-DENFIS model exhibits as far as four time smaller forecasting error that the VECM. It also produces statistically significant results that corroborate with the existing literature on the inefficiency of monetary exchange rate models to describe the evolution of exchange rates.

In Section 2 we review the relevant literature on monetary exchange rate models, while in Section 3 we briefly present the SVR-DENFIS framework. Section 4 discusses the dataset and the different inflation expectations examined in the paper. Section 5 reports the empirical findings based on the VECM and the SVR-DENFIS methodologies, while Section 6 concludes.

2 Literature review

After the breakdown of the Bretton Woods system, a number of monetary exchange rate models were proposed, linking exchange rate evolution to fundamentals. In this paper, we empirically test four of the most influential such models; the flexible price monetary model under Frenkel (1976) and Bilson (1978) and the sticky-price model as proposed by Dornbuch (1978) and Frankel (1979). The flexible price monetary model of Frenkel (1976) has been the workhorse for exchange rate economics for many years. It suggests that an increase in the money supply causes a direct and proportionate depreciation of the exchange rate, while it also implies a negative relationship between the exchange rate and the domestic GDP. On the other hand, the inflation rate differential is supposed to have a negative impact on a country’s exchange rate, with a rise to the former leading to the depreciation of the latter. Bilson (1978) builds on the aforementioned framework, suggesting that a rise in the domestic interest rate leads to an exchange rate depreciation, without including the inflation differential in the model’s structure. On a different path, Dornbuch’s (1978) sticky-price model states that under perfect capital mobility all prices are sticky. They are determined in the short-run by the expectations augmented Phillips curve and monetary policy is the main driver of exchange rate evolution. He argues in contrast to the flexible price model that an increase in the domestic interest rate will appreciate the domestic exchange rate. Finally, the interest rate differential model of Frankel (1979) combines inflationary expectations with the model proposed by Dornbuch, claiming that a rise in domestic inflation will lead to exchange rate depreciation.

The potential usefulness of these models in conducting monetary policy led to extensive research for their empirical confirmation. Chinn (2007a) examines the Malaysian Ringgit/USD and Phillipines Peso/USD (Chinn, 2007b) exchange rates, providing empirical validation of Bilson's suggestions. Miyakoshi (2000) also finds similar results for the Korean Won/German Mark and the Korean Won/Japanese Yen. Evidence in favor of Bilson's monetary exchange rate model can also be found in the work of Cushman (2007) for the Canadian Dollar/USD and Loria *et al.* (2009) for the Mexican Peso/USD. Within a similar research framework, Frenkel and Koske (2004) test monetary exchange rate models on various currencies traded with the Euro. They conclude that the inferred model structure is different for each currency, but overall, macroeconomic variables possess forecasting potential. Under a portfolio perspective, Adhyankar *et al.* (2005) detect higher returns in investing portfolios that are built using monetary models of exchange rates than portfolios based on random selection. Recently, Della Corte and Tsiakas (2011) extend the research to dynamic portfolios changing ratios over time for nine currencies. Constructing the portfolio according to the evolution of basic macroeconomic variables achieves higher and more sustainable returns over all other alternative approaches they use. Overall, Engel and West (2005) show that on the long run, there is adequate evidence in support of using monetary exchange rate models for forecasting the behavior of foreign exchange markets.

3 Methodology

3.1 Support Vector Regression (SVR)

The Support Vector Regression is a direct extension of the classic Support Vector Machine algorithm. The specific machine learning methodology has attracted significant interest in forecasting economic and financial time series (Rubio *et al.*, 2011; Härdle *et al.*, 2009; Öğüt *et al.*, 2012; Khandani *et al.*, 2010; Papadimitriou *et al.*, 2014, Plakandaras *et al.*, 2014), though in this paper we use it for economic modelling. The algorithm proposed by Vapnik *et al.* (1992) and latter extended by Cortes and Vapnik (1995) originates from the field of statistical learning. When it comes to regression, the basic idea is to find a function that has at most a predetermined deviation from the actual values of the dataset. In other words, point errors are not of interest as long as they don't violate a predefined threshold ε; only errors higher than ε are penalized. The vectors that bound the "error tolerance band" are identified through a minimization procedure and are called the Support Vectors (SV).

One of the main advantages of SVR in comparison to other machine learning techniques is that it yields a convex minimization problem with a unique global minimum, avoiding local minima. The model is built in two steps: the training and the testing step. In the training step, the largest part of the dataset is used for the estimation of the Support Vectors that define the band. In the testing step, the generalization ability of the model is evaluated by checking the model's performance in the small subset that was left aside during training. Using cross-validation techniques a universal and not sample-specific solution (overfitting) is achieved.

For a training dataset $D = [(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \dots .(\boldsymbol{x}_n, y_n)], \boldsymbol{x}_i \in \mathbb{R}^m, y_i \in \mathbb{R}, i = 1,2, \dots . n$, where $\boldsymbol{x}_i$ is a vector of independent variables and y_i is the dependent variable the linear regression function takes the form of $y = f(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + b$. This is achieved by solving:

$$\min\left(\frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{\iota=1}^{n}(\zeta_i + \zeta_i^*)\right) \tag{1}$$

$$\text{subject to}\begin{cases} y_i - (\boldsymbol{w}\boldsymbol{x}_i + b) \leq \varepsilon + \zeta_i \\ (\boldsymbol{w}\boldsymbol{x}_i + b) - y_i \leq \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \geq 0 \end{cases}$$

where ε defines the width of the tolerance band, and ζ_i, ζ_i^* are slack variables controlled through a penalty parameter C (see Figure 1). All the points inside the tolerance band have $\zeta_i, \zeta_i^* = 0$. System (1) describes a convex quadratic optimization problem with linear constraints and it has a unique solution. The first part of the objective function controls the generalization ability of the regression, by imposing the "flatness" of our model controlled through the Euclidean norm $\|\boldsymbol{w}\|$. The second part of the objective function controls the regression fit to the training data (by increasing C we penalize with a bigger weight any point outside the tolerance band i.e. with $\zeta_i \geq 0$ or $\zeta_i^* \geq 0$). The key element in the SVR concept is to find the balance between the two parts in the objective function that are controlled by the ε and C parameters.

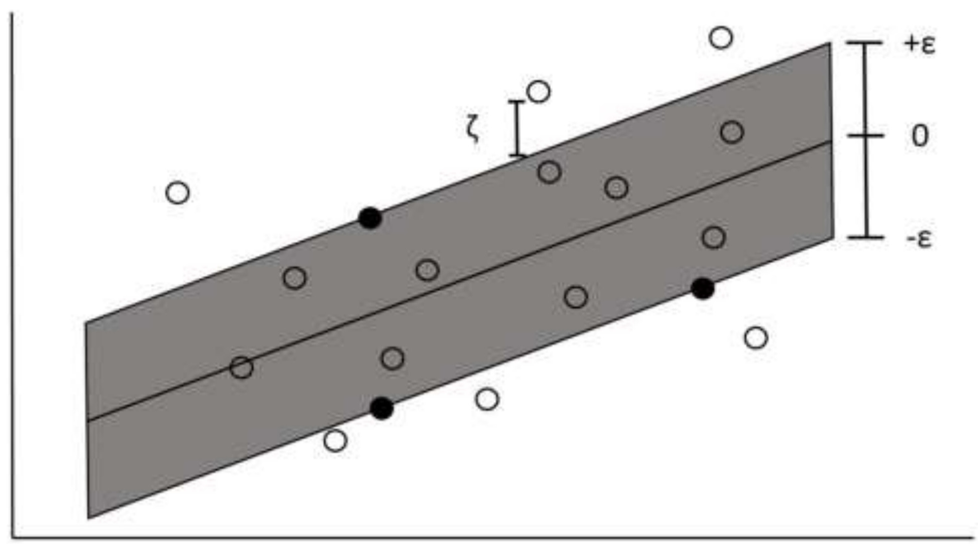

Figure 1: Upper and lower threshold on error tolerance indicated with letter ε. The boundaries of the error tolerance band are defined by the Support Vectors (SVs) denoted with the black filled points. Forecasted values greater than ε get a penalty ζ according to their distance from the tolerance accepted band.

Using the Lagrange multipliers in System (1) the solution is given by:

$$\boldsymbol{w} = \sum_{i=1}^{n}(a_i - a_i^*)\boldsymbol{x}_i \tag{2}$$

and

$$y = \sum_{i=1}^{n}(a_i - a_i^*)\boldsymbol{x}_i^T\boldsymbol{x} \tag{3}$$

with the coefficient α_i, $a_i^* = 0$ for all non SVs. Thus, the SVR model is defined solely by its SVs.

The underlying data generating processes of real life phenomena are rarely linear. Thus formulating linear models to describe them often generate simplistic approximations. This is the reason that the SVM/SVR is always coupled with the "kernel trick" that follows the projection idea while ensuring minimum computational cost: the dataset is mapped in an inner product space, where the projection is performed using only dot products within the original space through special "kernel" functions, instead of explicitly computing the mapping of each data point. When the kernel function is non-linear, the produced SVR model is non-linear as well

In our empirical estimations we employed four alternative kernels: the linear, the radial basis function (RBF), the sigmoid and the polynomial. The mathematical representation of each kernel is:

Linear

$$K_1(\boldsymbol{x}_1, \boldsymbol{x}_2) = \boldsymbol{x}_1^T\boldsymbol{x}_2 \tag{4}$$

RBF

$$K_2(\boldsymbol{x}_1, \boldsymbol{x}_2) = e^{-\gamma\|x_1 - x_2\|^2} \tag{5}$$

Polynomial

$$K_3(\boldsymbol{x}_1, \boldsymbol{x}_2) = (\gamma\boldsymbol{x}_1^T\boldsymbol{x}_2 + r)^d \tag{6}$$

Sigmoid

$$K_4(\boldsymbol{x}_1, \boldsymbol{x}_2) = \tanh(\gamma\boldsymbol{x}_1^T\boldsymbol{x}_2 + r) \tag{7}$$

with factors *d*, *r*, *γ* representing kernel parameters.

3.2 Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS)

The main disadvantage of the SVR methodology is that it does not offer a readily available analytical form of the trained model. In order to extract the fitted coefficients we adopt the framework proposed by Farquad *et al.* (2011) and use a Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS) system. The DENFIS proposed by Kasabov and Song (2002) belongs to the broader category of Evolving Inference Systems. The basic notion behind DENFIS is to classify all observations into clusters and extract fuzzy rules during classifications. After the initial classification of a first sub-sample of data the initially extracted fuzzy rules are updated (evolved) with the classification of new data and reiteration over the entire up to that point dataset. Then, based on the extracted fuzzy rules it develops a parametric linear function that models the structure of the dependent to the independent variables. For $x_1, x_2, \dots\dots, x_n$ independent input variables and *y* the dependent one, the inference engine of DENFIS is composed by *m* fuzzy rules where *m* is less or equal to the number of observations *n*. An extracted fuzzy rule FR_m has the form:

$$FR_m\text{: } if\ \boldsymbol{x}_1 is\ R_{m1}\ and\ \boldsymbol{x}_2\ is\ R_{m2}\ and\ \dots\dots.. and\ \boldsymbol{x}_n\ is\ R_{mn}\ then\ y = f_m(\boldsymbol{x}_1, \boldsymbol{x}_2, \dots., \boldsymbol{x}_n) \tag{8}$$

In DENFIS, R_{ij} are Gaussian Membership Functions (GMF), as noted in equation (9):

$$R_{ij}(x) = exp\left(\frac{-u(x-c)^2}{\sigma^2}\right) \tag{9}$$

The three parameters of the system are: the constant u, the parameter c which represents the cluster center for the certain GMF, and σ representing the GMFs (clusters) width.

As mentioned in section 3.1 the SVR model depends solely on the Support Vectors (SVs) that define the "tolerance band", with the coefficient a for all non SVs equal to zero. So, in order to infer upon the SVR model's structure we only need to evaluate the forecasted values of the SVR model on the SVs. The overall procedure of the hybrid SVR-DENFIS model is depicted in Figure 2.

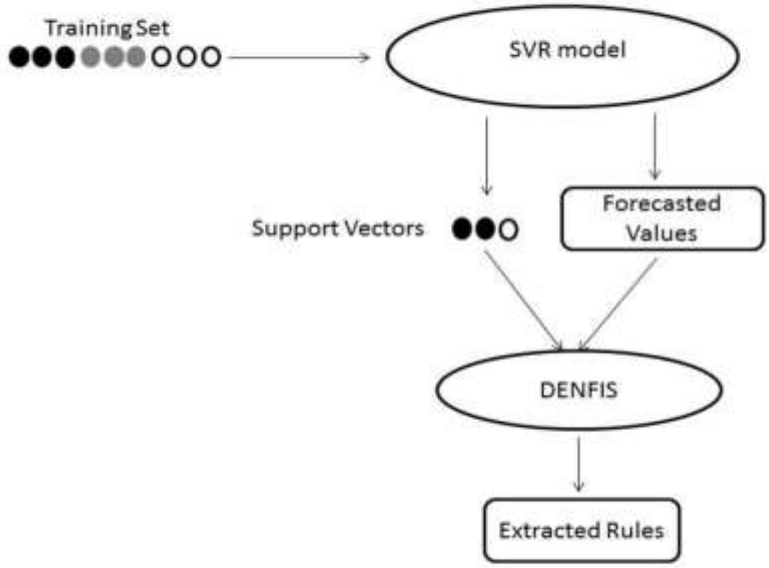

Figure 2: Overview of the DENFIS setup. After defining the SVR model with the lowest MAPE, Support Vectors and forecasted values are fed into a DENFIS for inferring the model structure.

4 Data and Methodology

4.1. The Data

In order to construct the variable differentials we compile data for Norway and the U.S. for the money supply (M2), the Norwegian interbank overnight interest rate, the real

GDP, the expected inflation in five alternative approximations, and real oil prices[3]. All data are quarterly from 1997Q1 to 2008Q2 and are compiled from the International Financial Statistics database of the International Monetary Fund, with the exception of forward exchange rates (considered as a potential measure of inflation expectation) and oil prices that are from the EcoWin Reuters database. All variables are transformed into natural logarithms with the exception of the interest rates and the inflation expectations.

4.2. The Empirical Model

According to Engel and West (2005), macroeconomic variables appear to have a significant ability to forecast exchange rates in the long run. We apply the Support Vector Regression methodology on a monetary model of a general form (Chinn, 2007a), which takes into account the differences in macroeconomic fundamentals between the U.S. and Norway:

$$\begin{aligned}\Delta s_{t+1} = c_o &+ \beta_1 \Delta s_t + \beta_2 \Delta(m_t - m_t^*) + \beta_3 \Delta(y_t - y_t^*) + \beta_4 \Delta(r_t - r_t^*) + \beta_5 \Delta(\pi_t - \pi_t^*) \\ &+ \beta_6 \Delta oilp_t + \beta_7 T \\ &+ e_t \end{aligned} \tag{10}$$

where s is the nominal exchange rate (i.e. NOK per USD), c_o is a constant, T is a time trend, m is the money supply (M2) , y is the real GDP, r is the nominal interest rate, *oilp* is the oil price adjusted for the Norwegian CPI and π is the expected inflation rate. An asterisk denotes a U.S. variable.

4.3. Expected Inflation Approximations

To approximate the unobserved expected inflation for both countries we use five alternatives. A simple common approximation is to model inflation expectations with an autoregressive trend. Following the literature (Chinn, 2007a) we choose an AR(4) model on the growth rate of the CPI. Extending the above framework, we apply an ARMA(p,q) model fitted on the growth rate of the CPI, with the order of the lag structure and the moving average term determined by the Schwartz (1978) Information Criterion. Furthermore, according to De Grauwe (1996), oil exporting countries are supposed to experience exchange rate changes in line with oil price fluctuations (i.e. when oil prices rise their exchange rate appreciates and vice versa). In order to observe the exogenous effect of oil price on the exchange rate, we also construct the above AR(4) and ARMA(p,q) inflation expectation models for a CPI that excludes energy prices. By doing so, we are able to directly capture the effect of oil price fluctuations on exchange rate determination.

Svensson (1994) proposes that forward rates can be used as a proxy to inflation expectations and Kloster (2000) argues that the forward rate plays a crucial role on Norges's Bank Inflation Report. In other words, differences between the Norwegian and the U.S. dollar forward rates may be interpreted as differences on inflation expectations between the two economies. Thus we can model the unobserved inflation expectation as it

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[3] The oil prices are an index, which has 2005 as base year and it is the arithmetic mean of the spot prices of Brent, West Texas Intermediate and Dubai Fateh. Moreover, oil prices are calculated in Norwegian Kroner dividing by the consumer price index in Norway.

is captured in the forward exchange rate. To incorporate such a perspective, inflation expectations are measured with the one year forward contract to be paid (starting) two years ahead, using the two year and three year swap rate for Norway and the U.S. The inflation approximations used are summarized in Table 1.

Table 1: Inflation Expectation Approximations

Model Name	Approximation
Model 1	Inflation expectations proxied by the preceding four quarters' growth in CPI
Model 2	Inflation expectations proxied by the preceding four quarters growth in CPI (less energy)
Model 3	Inflation expectations proxied by CPI inflation forecasts from an ARMA(1,1) model for Norway and an ARMA (2,2) model for the U.S.
Model 4	Inflation expectations proxied by CPI-less energy inflation forecasts from ARMA (2,2) models for both countries
Model 5	Inflation expectations proxied by 1 year forward rate 2 years ahead

Additionally, each SVR model is trained using the four kernels discussed. This results in twenty alternative empirical models. We perform model optimization by measuring the one-period-ahead forecasting accuracy according to the Mean Absolute Percentage Error (MAPE) and the Directional Symmetry (DS) metrics. The relevant formulas are:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

$$\mathrm{DS} = \frac{100}{n}\sum_{i=1}^{n} d_i \text{ , } where\ d_i = \begin{cases} 1\ if\ (y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0 \\ 0\ otherwise \end{cases} \tag{12}$$

where $\hat{y}_i$ is the forecasted exchange rate for period i, y_i is the actual value and n is the total number of the observations used. The MAPE measures the percentage of the absolute error in forecast, while DS measures the percentage of the times we correctly forecast the future direction of the exchange rate and are both independent of the variables' magnitude. Directional forecasting is of key interest to market participants, since trading decisions on whether to go long or short on a currency depend on whether an appreciation or depreciation is expected rather than the exact future value of the exchange rate.

5 Empirical Results

The optimal parameters for each kernel and for all five inflation expectation models are selected through an exhaustive search procedure that results in training 6.4×10^7 models in total. From these the optimum models for each kernel and inflation approximation model are selected based on the MAPE criterion.

Since our research was initially inspired by Papadamou and Markopoulos (2012) we test the performance of our approach with the adopted in that paper VECM models. We test for unit roots and all series are found to be I(1) in the levels and I(0) in first differences. One cointegrating vector is detected and 5 VECM models on first differences are constructed, one for each inflation approximation model [4]. For the selection of the optimum lag structure of the VAR model, we report five widely used lag selection criteria: the Swartz (1978) Information Criterion (SIC), the Likelihood Ratio test (LR) [Neyman and Pearson, 1933], the Final Prediction Error (FPE) [Akaike, 1969], the Akaike (1974) Information Criterion (AIC), and the Hannan-Quinn (1979) Information Criterion (HQ). In what follows we use the lag structure selected by the SIC, since it leads to a more parsimonious model. The lag selection criteria results are reported in Table 2.

Table 2: VAR Lag Selection Criteria

VAR Lags	LR	FPE	AIC	SIC	HQ
Model 1	417.235 (1)	1.49e-13 (1)	-12.630 (3)	-10.802 (1)	-11.889 (1)
Model 2	68.281 (2)	1.02e-14 (2)	-15.463 (3)	-12.937 (1)	-14.132 (3)
Model 3	71.655 (3)	2.64e-14 (3)	-14.384 (3)	-11.756 (1)	-13.193 (2)
Model 4	67.879 (2)	1.16e-14 (2)	-15.322 (3)	-12.722 (1)	-14.019 (2)
Model 5	78.588 (2)	3.21e-15 (2)	-16.472 (2)	-13.738 (1)	-15.289 (2)

Note: All tests are conducted at the 5% level of significance. Selected lags appear in parentheses.

The empirical results of the best trained SVR and VECM models are reported in Table 3.

Table 3: Comparison of Empirical Results based on MAPE

Inflation Expectation Approximation	SVR				VECM
	Linear kernel	RBF kernel	Polynomial kernel	Sigmoid kernel	
Model 1	1.511	0.595	1.311	1.249	1.062
Model 2	1.488	**0.149**	1.383	0.921	0.985
Model 3	1.427	0.358	1.177	1.801	1.090
Model 4	1.353	1.106	1.183	1.453	1.030
Model 5	1.505	1.278	1.263	1.407	**0.840**
RW model			1.477		

Note: Best models for the SVR and the VECM models are marked in bold. The numbers show percentages.

[4] Due to space limitations and since the VECM methodology is common in the literature all results from unit roots and cointegrating vectors tests are not reported here and are available upon request.

We observe that the best overall fit as it is measured by the MAPE forecasting criterion is achieved with an SVR model employing the RBF kernel and coupled with the inflation expectations produced by Model 2. The corresponding MAPE value is 0.149% while the best VECM model is the one using Model 5 specification for the expected inflation with a MAPE of 0.840%. The results show that the best VECM model produces more than five times higher forecasting error (0.840%) than the best SVR (0.149%). The SVR model with the best fit on the NOK/USD exchange rate is the one that uses the AR(4) on the growth rate of CPI (less energy) inflation expectation (Model 2). Thus, fundamentals can best describe the evolution of the exchange rate when we exclude the exogenous effect of oil price fluctuations from the inflation differential as oil prices are determined internationally and not domestically. This finding is rather interesting. It suggests that a significant part of the fitting error between Models 1 and 2 can be attributed to the effect of oil prices on inflation expectations. In other words, if we isolated the CPI from the effect of oil price fluctuations, we observe that the CPI acts as Norway was not an oil exporting country. This finding corroborates to the successful role of the specific oil fund in isolating the domestic demand from oil price fluctuations.

Table 4: Comparison of Empirical Results based on DS

	SVR				VECM
Inflation Expectation Approximation	Linear kernel	RBF kernel	Polynomial kernel	Sigmoid kernel	
Model 1	64.286	85.714	64.286	78.571	69.048
Model 2	71.429	**97.619**	66.667	78.571	76.190
Model 3	73.171	90.244	68.293	78.049	75.610
Model 4	68.293	82.927	65.854	75.610	**78.049**
Model 5	66.667	76.190	76.190	78.571	71.429
RW model	66.667				

Note: Best models for the SVR and the VECM models are marked in bold.

From Table 4 we observe that in terms of directional accuracy, the SVR model employing the RBF kernel under Model 2 inflation expectations forecasts almost perfectly the future directional evolution of the exchange rate, while the best VECM model (under Model 4 inflation expectations) is almost 20% less accurate. In Figure 3 we present the best SVR and VECM models in terms of MAPE criterion, along with the actual NOK/USD exchange rate and a random walk. We limit the time window of the diagram only to the last two years in order for the SVR model to be visible.

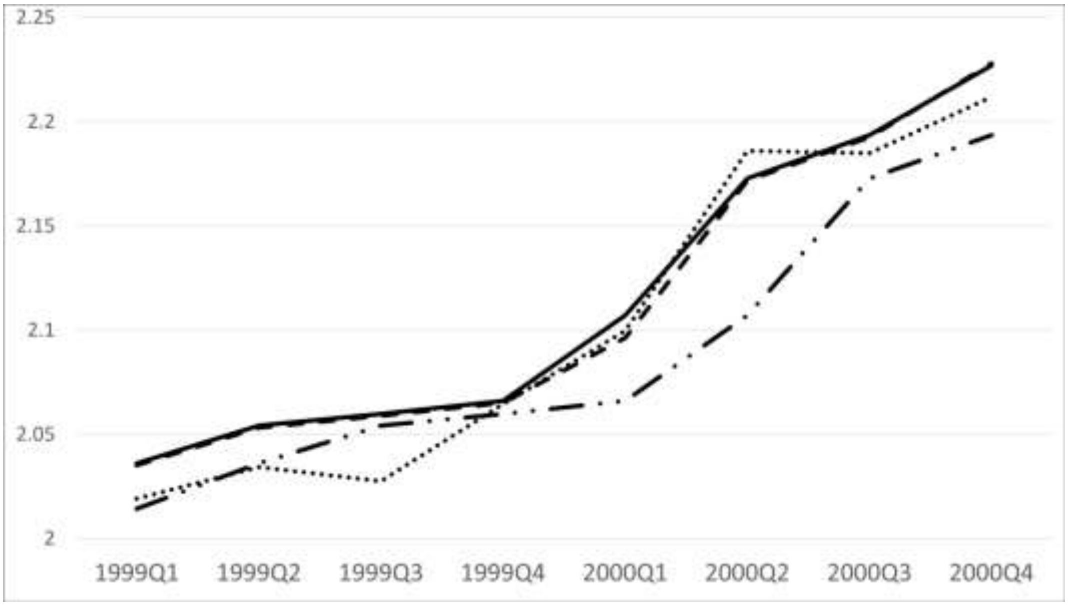

Figure 3: Representation of the best VECM, SVR and RW model forecasts and the actual values of the exchange rate for a time window of two years.

When training repeatedly a large number of models on the same dataset there is always the possibility that the reported results may be due to chance and not stemming from the actual forecasting ability of the model. This phenomenon is reported in the literature as data mining or data snooping (Cowles, 1933). To mitigate the possibility of this in our study we evaluate all models with the *Reality Check* (RC) proposed by White (2000). This tests the null hypothesis of equal forecast ability between the model under evaluation and a benchmark Random Walk (RW) model against the alternative of a higher forecasting ability of the former[5]. In other words we test the forecasting superiority of the trained models over the RW model, building on the critique on the paper of Messe and Rogoff (1983). In doing so, White (2000) proposes the application of the stationary bootstrap procedure by Politis and Romano (1994) and the extraction of asymptotic *p*-values for the evaluation of the null hypothesis. For selecting the optimal average block size of the stationary bootstrap we follow the procedure suggested in Politis *et al* (2009)[6]. The *p*-values of the RC test are reported in Table 5.

[5] For the RC we implemented the matlab code provided by Arnout Tilgenkamp available at http://www.mathworks.com/matlabcentral/fileexchange/34306-white-reality-check

[6] For the optimal average block size selection we implemented the matlab code provided by Andrew Patton available at http://public.econ.duke.edu/~ap172/code.html.

Table 5: Comparison of Empirical Results

Inflation Expectation Approximation	Kernel	SVR	VECM
		RC (p-value)	RC (p-value)
Model 1	Linear	0.326	0.000***
	RBF	0.000***	
	Sigmoid	0.000***	
	Polynomial	0.000***	
Model 2	Linear	0.043**	0.735
	RBF	0.000***	
	Sigmoid	0.024**	
	Polynomial	0.000***	
Model 3	Linear	0.075*	0.000***
	RBF	0.000***	
	Sigmoid	0.912	
	Polynomial	0.000***	
Model 4	Linear	0.050*	0.698
	RBF	0.000***	
	Sigmoid	0.006***	
	Polynomial	0.000***	
Model 5	Linear	0.990	0.000***
	RBF	0.980	
	Sigmoid	0.987	
	Polynomial	0.966	

Note: ***, ** and * denote rejection of the null hypothesis of the RC test of equal predictive ability of the model in comparison to the RW model in 1%, 5% and 10% respectively.

According to this robustness test, for both optimal models (SVR and VECM) we can strongly reject the null hypothesis of equal forecasting ability with the benchmark RW model. Of course there is an infinite number of comparisons that we could perform by considering the VECM models as the benchmark model and the SVR model as the alternative. Considering the most accurate SVR-RBF model (under AR-less energy inflation expectations) and the most accurate VECM (under forward exchange rate inflation expectations) we reject the null hypothesis of equal forecasting ability at 1% level of significance (p-value=0.0023).

After the selection of the best SVR model in terms of fitting the data, we derive its model representation with DENFIS. As the popular alternative monetary exchange rate models proposed in the literature are linear, we limit the extracted model representations only to linear ones. DENFIS extracted 12 fuzzy rules reported in Appendix A. The extracted coefficients based on the model structure of Equation (10) are reported in Table 5. In order to compute the standard error and the *t*-statistic for each coefficient we regress the fitted values $\hat{y}_i$ plus a random error produced by bootstrapping the residuals of the DENFIS model on the fixed coefficient matrix (the values of the coefficient matrix produced by DENFIS beforehand) to obtain bootstrap replications of the regression coefficients[7].

Table 6: SVR-DENFIS coefficient values

	C	s_t	$m_t - m_t^*$	$y_t - y_t^*$	$r_t - r_t^*$	$\pi_t - \pi_t^*$	$oilp_t$
Coefficient	0.360	0.540	0.550	-0.120	0.070	-0.800	-0.030
Standard Error	0.106	0.018	0.058	0.118	0.001	0.003	0.004
p-value	0.002***	0.000***	0.000***	0.315	0.000***	0.000***	0.000***

Note: *** denotes statistical significance at 1% level of significance.

In Table 5 we observe that the signs of the coefficients for the money supply and output differentials are in line with all structural monetary exchange rate models described in the literature, i.e. the flexible price, the sticky price, and the interest rate differential monetary exchange rate model, although the value for the money supply differential coefficient is significantly different from what is expected (see Table 7)[8]. The reported *p*-values show that all coefficients with the exception of the output differential are strongly significant at the 1% level of confidence.

Table 7: Model Coefficients as expected by theory

Coefficients	$m_t - m_t^*$	$y_t - y_t^*$	$r_t - r_t^*$	$\pi_t - \pi_t^*$
Frenkel model	+1	<0	0	>0
Bilson model	+1	<0	>0	0
Dornbusch model	+1	<0	<0	0
Frankel model	+1	<0	<0	>0
Best VECM[9]	>0**	<0	>0	>0
SVR-DENFIS	>0***	<0	>0***	<0***

Note: **, and *** denotes statistical significance at 5 % and 1% level of significance.

The sign of the coefficient for the interest rate differential of the SVR-DENFIS model is consistent only with the model proposed by the flexible price monetary model of Bilson (1978). It states that a rise in the current domestic interest rate will cause a depreciation in the future. This finding corroborates studies on the CAD/USD (Cushman, 2007), the MXN/USD (Loria *et al.*, 2009), and Asian currencies (Chinn, 2007a, b), exchange rates.

[7] We do not report the trend coefficient, since it is irrelevant to our examination regarding monetary exchange rate models.
[8] The statistical test that the money supply differential coefficient is equal to one is strongly rejected (t-statistic=-7.748/p-value=0.000)
[9] For a detailed exposition of the VECM models see Papadamou and Markopoulos (2012).

The CPI (less energy) inflation rate differential has a negative and sizeable effect on the exchange rate (a coefficient of -0.800), far more influential than all other variables of the model. Moreover, the positive coefficient of the first lag of the exchange rate implies persistence in exchange rate movements; i.e. ceteris paribus NOK exhibits a habit formation (Backus *et al.*, 1993). The VECM model does not provide statistically significant evidence in favor of any monetary exchange rate model. This fact is another indication of the inability of the methodology to describe a long-run equilibrium relationship within the examined data span.
Focusing on the effect of oil price on the depended variable, we observe a small negative but highly significant relationship between the exchange rate evolution and oil price fluctuations, corroborating the result of Akram (2004) who detects a weak long-run relationship between the NOK/USD rate and oil price fluctuations. The sign of the oil price is negative indicating that a surge in oil prices leads to the appreciation of the NOK with respect to the USD. The above finding is rather interesting since Norway is an oil exporting country and we would expect that oil price fluctuations would strongly affect the exchange rate (De Grauwe, 1996). The detected weak relationship may be attributed to the existence of the Government Pension Fund that aims to absorb the effects of oil price fluctuations so that domestic macroeconomic variables are more isolated to such exogenous shocks. Overall, the signs of the coefficients from the SVR-DENFIS model provide some evidence in favor of Bilson's (1978) monetary exchange rate model with the addition of a statistically significant negative inflation rate expectations differential coefficient. Nevertheless, the oil price coefficient, along with the use of a CPI(less energy) approximation of inflation rate expectations indicates a weak but statistically significant effect of oil price fluctuations on the NOK/USD determination.

6 Conclusion

In this paper we employ a two stage SVR-DENFIS methodology as an alternative to the standard VECM models used in the relevant literature. We empirically compare the ability of these methodologies on the basis of a general monetary exchange rate model for the NOK/USD exchange rate. Inflation expectations are approximated by five alternative models. The results show that the hybrid SVR-DENFIS model coupled with the RBF kernel describes more accurately the evolution of the NOK/USD exchange rate. The best forecasting model is the one employing inflation expectations approximated by an AR(4) specification of the CPI (less energy) which isolates oil price fluctuations from inflation and thus allowing to observe directly the effect on the NOK/USD rate. The resulting SVR-DENFIS model structure provides some evidence in favor of Bilson's (1978) monetary exchange rate model with the addition of a statistically significant negative coefficient on the inflation rate expectations differential, while reporting a weak long-run relationship between oil price fluctuations and exchange rate determination. The VECM model failed to provide statistically significant evidence in favor of any monetary exchange rate model. Although Norway is an oil exporting country, this detected weak long-run relationship could be attributed to the Government Pension Fund that absorbs oil price fluctuations providing stability to the Norwegian economy. Overall we do not find explicit evidence in favor of a specific monetary exchange rate model proposed in the literature, but the use of the SVR-DENFIS methodology moves further than the typical econometric approach.

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Appendix A

In Table A-1 we report the extracted fuzzy rules as we update the Gaussian functions by adding one cluster center at a time. Rule 12 is the final extracted rule for the entire dataset.

Table A-**1**: First order TSK rules extracted by DENFIS

Rule	**Antecedent part**	**Model Specification**
1	if X1 is (0.70 0.81 0.92)	Y = 0.17
	X2 is (0.53 0.64 0.75)	+ 0.11 × X1
	X3 is (0.37 0.48 0.59)	+ 0.42 × X2
	X4 is (0.23 0.34 0.45)	+ 0.49 × X3
	X5 is (0.39 0.50 0.61)	- 0.41 × X4
	X6 is (0.70 0.81 0.92)	+ 0.03 × X5
		+ 0.04 × X6
2	if X1 is (0.53 0.64 0.75)	Y = 0.88
	X2 is (0.21 0.32 0.43)	- 0.17 × X1
	X3 is (0.56 0.67 0.78)	+ 0.09 × X2
	X4 is (0.18 0.29 0.40)	+ 0.23 × X3
	X5 is (0.36 0.47 0.58)	- 0.50 × X4
	X6 is (0.56 0.67 0.78)	- 0.80 × X5
		+ 0.38 × X6
3	if X1 is (0.46 0.57 0.68)	Y = 0.24
	X2 is (0.36 0.47 0.58)	+ 0.19 × X1
	X3 is (0.21 0.33 0.44)	- 0.09 × X2
	X4 is (0.28 0.39 0.50)	+ 0.45 × X3
	X5 is (0.49 0.60 0.71)	+ 0.47 × X4
	X6 is (0.51 0.62 0.73)	- 0.48 × X5
		+ 0.25 × X6
4	if X1 is (0.48 0.59 0.70)	Y = -1.49
	X2 is (0.56 0.67 0.78)	+ 1.03 × X1
	X3 is (0.52 0.63 0.74)	+ 0.85 × X2
	X4 is (0.67 0.78 0.89)	+ 1.10 × X3
	X5 is (0.63 0.74 0.85)	+ 0.10 × X4
	X6 is (0.23 0.34 0.45)	- 0.03 × X5
		+ 0.54 × X6
5	if X1 is (0.67 0.78 0.89)	Y = -1.03
	X2 is (0.67 0.78 0.89)	+ 1.22 × X1
	X3 is (0.34 0.45 0.56)	+ 0.57 × X2

	X4 is (0.09 0.20 0.31)	+ 1.07 × X3
	X5 is (0.63 0.74 0.85)	- 0.03 × X4
	X6 is (0.58 0.69 0.80)	+ 0.22 × X5
		- 0.28 × X6
6	if X1 is (0.36 0.47 0.58)	Y = 1.37
	X2 is (0.30 0.41 0.52)	- 0.17 × X1
	X3 is (0.57 0.68 0.79)	- 0.47 × X2
	X4 is (0.26 0.37 0.48)	+ 0.19 × X3
	X5 is (0.10 0.21 0.32)	- 0.71 × X4
	X6 is (0.40 0.51 0.62)	- 0.77 × X5
		- 0.05 × X6
7	if X1 is (0.14 0.25 0.36)	Y = 1.11
	X2 is (0.61 0.72 0.83)	+ 0.88 × X1
	X3 is (0.59 0.70 0.81)	- 0.51 × X2
	X4 is (0.30 0.41 0.52)	+ 0.32 × X3
	X5 is (0.49 0.60 0.71)	- 1.01 × X4
	X6 is (0.66 0.77 0.88)	+ 0.02 × X5
		- 0.60 × X6
8	if X1 is (0.17 0.28 0.39)	Y = 1.39
	X2 is (0.05 0.16 0.27)	+ 0.11 × X1
	X3 is (0.44 0.55 0.66)	- 0.50 × X2
	X4 is (0.23 0.34 0.45)	+ 0.24 × X3
	X5 is (0.44 0.55 0.66)	- 0.83 × X4
	X6 is (0.61 0.72 0.83)	- 1.04 × X5
		- 0.12 × X6
9	if X1 is (0.46 0.57 0.68)	Y = -0.19
	X2 is (0.42 0.53 0.64)	- 0.13 × X1
	X3 is (0.33 0.44 0.55)	+ 0.50 × X2
	X4 is (0.23 0.34 0.45)	+ 0.86 × X3
	X5 is (0.48 0.59 0.70)	- 0.16 × X4
	X6 is (0.22 0.33 0.44)	- 0.11 × X5
		+ 0.45 × X6
10	if X1 is (0.49 0.60 0.71)	Y = -0.25
	X2 is (0.52 0.63 0.74)	+ 0.52 × X1
	X3 is (0.63 0.74 0.85)	+ 0.74 × X2
	X4 is (0.09 0.20 0.31)	+ 0.59 × X3
	X5 is (0.53 0.64 0.75)	- 0.91 × X4
	X6 is (0.14 0.25 0.36)	- 0.29 × X5
		+ 0.31 × X6

11	if X1 is (0.39 0.50 0.61)	Y = 1.75
	X2 is (0.75 0.86 0.97)	+ 0.45 × X1
	X3 is (0.53 0.64 0.75)	- 0.77 × X2
	X4 is (0.18 0.29 0.40)	+ 0.72 × X3
	X5 is (0.09 0.20 0.31)	- 1.57 × X4
	X6 is (0.80 0.91 1.02)	+ 0.34 × X5
		- 1.22 × X6
12	if X1 is (0.11 0.22 0.33)	Y = 0.36
	X2 is (0.71 0.82 0.93)	+ 0.54 × X1
	X3 is (0.61 0.72 0.83)	+ 0.55 × X2
	X4 is (0.32 0.43 0.54)	- 0.12 × X3
	X5 is (0.70 0.81 0.92)	+ 0.07 × X4
	X6 is (0.31 0.42 0.53)	- 0.03 × X5
		- 0.80 × X6