UNIVERSITÀ CATTOLICA del Sacro Cuore

Dipartimento di Economia Internazionale, delle Istituzioni e dello Sviluppo (DISEIS)

WORKING PAPER SERIES

WP 1901

January, 2019

Statistical Learning and Exchange Rate Forecasting

Emilio Colombo, Matteo Pelagatti

Prior to being published, DISEIS working papers are subject to an anonymous refereeing process by members of the editorial board or by members of the department.

DISEIS Working Papers often represent preliminary work which are circulated for discussion and comment purposes. Citation and use of such a paper should account for its provisional character. A revised version may be available directly from the author.

DISEIS WP 1901

DISEIS
Dipartimento di Economia Internazionale, delle Istituzioni e dello Sviluppo
Università Cattolica del Sacro Cuore
Via Necchi 5
20123
Milano

Statistical learning and exchange rate forecasting

Emilio Colombo*

DISEIS, Università Cattolica del Sacro Cuore

Matteo Pelagatti

DEMS, University of Milano-Bicocca

January 2019

Abstract

This study uses the most innovative tools recently proposed in the statistical learning literature to assess the ability of standard exchange rate models to predict the exchange rate in the short and long run. Our results show that statistical learning methods display impressive performances, consistently outperforming the random walk in forecasting the exchange rate at different forecasting horizons, with the exception of the very short term (a period of 1-2 months). We use these tools to compare the predictive ability of different exchange rate models and model specifications. We find that sticky price versions of the monetary model with the error correction specification exhibit the best performance. We also explore the functioning of statistical learning models by developing measures of variable importance and by analyzing the kind of relationship that links each variable with the outcome. This allows us to improve our understanding of the relationship between the exchange rate and economic fundamentals, which appears complex and characterized by strong non-linearities.

Keywords: Exchange Rate, Forecasting, Machine Learning

JEL codes: F37, C53

*Corresponding author, DISEIS, Università Cattolica del Sacro Cuore, Largo Gemelli 1, 20123 Milano, Italy. Email: emilio.colombo@unicatt.it. We thank Michele Rocca for research assistance and Patrizio Tirelli for useful comments.

1 Introduction

One of the most established puzzles in international finance is the inability of standard models to forecast the exchange rate, both in the short and long run. This is linked to another major puzzle in international finance known as the "exchange rate disconnect puzzle." Although not equivalent, the two puzzles are strongly related. The exchange rate forecasting puzzle dates back to the seminal work by Meese and Rogoff (1983), who showed that standard models of exchange rate were systematically outperformed by a random walk in out-of-sample forecasting. The second puzzle refers to "the exceedingly weak relationship (except, perhaps, in the longer run) between the exchange rate and virtually *any* macroeconomic aggregates" (Obstfeld and Rogoff, 2001).

This study attempts to address both these puzzles using tools having recently appeared in the statistical learning literature. Our aim is twofold. On the one hand, we aim to assess whether machine learning (ML) methods applied to standard exchange rate models are useful in (out-of-sample) forecasting of the exchange rate. On the other hand, by investigating the "black box" of ML tools[1] we improve our understanding of the link between macroeconomic fundamentals and the exchange rate implicit in statistical learning models.

We innovate with respect to the literature in several domains. First, we apply the most promising and innovative tools in the ML literature to a set of rather standard exchange rate models. Thus, our objective is not the out-of-sample prediction of the exchange rate *per se* but rather the assessment of exchange rate models through recent ML methods.

Second, we show that, with the exception of the very short run (1-2 months), ML models display impressive predictive abilities, consistently outperforming the random walk benchmark. These results are robust across countries, time, models, and forecasting horizons. Based on these results, we can confirm that fundamentals do matter in exchange rate forecasting.

Third, among our selection of ML algorithms, support vector machines emerge as the best performing method.

Fourth, we use statistical learning methods to compare the predictive ability of different exchange rate models and model specifications. We particularly select the regressors implied by four different exchange rate models and attempt to predict the forward dif-

[1]Throughout the paper, we will use the terms ML and Statistical Learning interchangeably and without loss of generality.

ference of exchange rates using the explanatory variables in difference or in levels. In the latter case, we assume that some kind of nonlinear error correction mechanism (ECM) may hold. Overall, we find that the sticky price version of the monetary model in ECM form achieves the best performance.

Finally, we look inside the best performing ML model by developing measures of variable importance consistent with our prediction scheme and by representing the partial relationship linking each regressor with the response variable. This is a major improvement with respect to the existing economic literature, where ML methods are generally treated as black boxes incapable of producing information on the factors that contribute the most to the predictive performance.

The remainder of the paper is structured as follows: Section 2 presents a brief overview of the relevant literature, Section 3 shows the motivation for the need to use statistical learning tools in the context of exchange rate forecasting. Section 4 presents the methodology and data. Section 5 illustrates the results and, finally, Section 6 concludes.

2 Related literature

The early literature on exchange rates modeling dates back to the work of Meade (1951) with the development of the Keynesian framework. However, it has been with the contribution of Mundell (1962, 1963) and Fleming (1962) that the Keynesian open economy model became the dominant framework in the literature. The demise of the Bretton Woods system spurred a new debate on both the theoretical and empirical side of the puzzle. On the theoretical side, the original Mundell-Fleming model has been modified to incorporate expectations in a truly asset market approach in a flexible (Frenkel, 1976; Mussa, 1976) or sticky price (Dornbusch, 1976; Wilson, 1979) setting. The standard model has also been modified to allow imperfect substitutability between domestic and foreign assets (Branson and Henderson, 1985). However, as soon as a sufficient amount of data from the floating period started to become available, exchange rate models struggled to find consistent empirical support, especially in out-of-sample forecasting. In particular, the empirical literature results were invalidated by the seminal contribution of Meese and Rogoff (1983), who found that standard exchange rate models had no predictive ability. Since then, outperforming the random walk has been a formidable challenge for any exchange rate model at most common forecasting intervals. On the theoretical side, advances have been made over time, with new Keynesian models (Obstfeld and Rogoff, 2001) providing microfoundations for open economy models; however, on the empirical side, the challenges remained unanswered. Some models, such as the Taylor rule (Molodtsova and Papell, 2009), appear more effective in the short run and monetary models display some predictive power in the long run (Cheung, Chinn, and Pascual, 2005; Mark, 1995), but the general picture is rather grim. Using the words of Rossi (2013) "None of the predictors, models, or tests systematically finds empirical support of superior exchange rate forecasting ability across all countries and time periods: when predictability appears, typically it does so occasionally for some countries and for short periods of time."

In asset prices models it may be natural to observe such empirical failures. Engel and West (2005) argue that if the discount factor is close to one and fundamentals follow a near unit root process, the exchange rate should manifest a near-random walk behavior resulting in little predictability, especially at short horizons.[2]

Nonetheless, most economists would agree that the relationship between exchange rate and fundamentals postulated by economic models should translate into models that can predict the exchange rate to some degree. This explains the almost obsessive interest of the economic literature in this topic: a simple Google Scholar search for "exchange rate forecast" yields more than 154,000 hits.[3]

3 Why statistical learning models?

A possible explanation for the empirical failure of standard exchange rate models to predict the exchange rate is that the tools used are not powerful and flexible enough to capture the complex relationship between exchange rate and fundamentals. For example, there is a growing body of literature highlighting the presence of non-linearities in exchange rate dynamics (Sarno, Valente, and Leon, 2006; Taylor, Peel, and Sarno, 2001).

Statistical learning tools are indeed extremely flexible methods that detect patterns in data and use them to make predictions. These patterns may be highly nonlinear and based on the interaction among variables. In the jargon of the ML literature, we use supervised learning techniques whose goal is to predict the value of a response variable (future increments of the exchange rate) using a set of input variables or *features* (fundamentals). "Supervised" refers to the fact that the presence of an observable re-

[2]In the long run, some studies found evidence of cointegration between the exchange rate and fundamentals (MacDonald and Marsh, 1997).

[3]The search was done on September 5th, 2018.

sponse variable guides the learning process.[4] ML tools are well-known in the scientific community as they have been applied to several fields, such as engineering, physics, and biology, since the early nineties. More recently, these tools have also gained popularity in the social sciences following the availability of large data sets, on which they can be successfully trained. Most ML applications in economics have been for purely predictive purposes[5] as these tools are extremely efficient in prediction.[6] Therefore, given the inability of standard models to predict the exchange rate, this is a perfect situation in which to apply ML methods.

However, the purpose of this study is not only prediction. We also use ML to improve our understanding of the exchange rate and of its relationship with economic fundamentals. In particular, we use ML methods to compare the predictive power of different exchange rate models and different model specifications. We then open the black box of these methods, unveiling some interesting findings, such as variable importance and the form of the interaction between fundamentals and exchange rates increments.[7]

Confining our study to standard exchange rate models also allows us to eliminate possible misconceptions about the application of ML in financial markets. As these tools are extremely efficient at detecting existing patterns in the data, in principle, they can capture the effect of any non-fundamental determinant of the exchange rate, the effect of possible non-rational behavior of market participants, or that of external factors, such as central bank intervention. In that context, statistical learning may be considered as a sophisticated variant of technical analysis. To preclude this type of interpretation, we apply ML only to traditional exchange rate models, thus not including past (lagged) prices and exchange rates, from which further patterns could be detected. Therefore, in our setting, ML algorithms can be viewed merely as flexible nonparametric statistical methods applied to otherwise standard exchange rate models.

[4]In unsupervised learning, there is no observable response variable and the techniques are designed to detect possible patterns that emerge in the input variables.

[5]There is an emerging literature on ML and casual inference well surveyed by Athey (2018).

[6]See Colombo, Forte, and Rossignoli (2018), Huerta, Corbacho, and Elkan (2013), and Papadimitriou, Gogas, and Stathakis (2014) for financial market forecasts and Holopainen and Sarlin (2017) for an application to early warning indicators.

[7]Our study differs substantially from Li, Tsiakas, and Wang (2015), who apply an elastic net to a *kitchen-sink* regression of all possible lagged fundamental variables. We apply a larger set of ML models to allow non-linearity and interactions in well-established exchange rate models but, in this study, we are not interested in finding the best predictive model using whatever information is available. Moreover, we delve deeper in explaining ML models.

4 Methods and data

4.1 Exchange Rate Models

Before we start the descriptions of the models, let us introduce some notation. Following Box et al. (2015), let Δ_k be the k-period *forward* difference (e.g., $\Delta_k x_t = x_{t+k} - x_t$), and ∇_k be the k-period *backward* difference (e.g., $\nabla_k x_t = x_t - x_{t-k}$). Let e_t denote the (log of) the exchange rate expressed in US dollars at the end of period t, and X_t be a set of fundamentals (to be defined below). Finally, let a "hat" over a variable denote cross country differentials (the United States is the reference country in our case), for example, $\hat{y} = y^i - y^{US}$.

We use different models of the exchange rate with different sets of variables as fundamentals. For each model, following Cheung, Chinn, and Pascual (2005) and Cheung et al. (2018), we estimate two versions: one is a model in difference form and the other is an error correction model. The latter approach allows the model to better incorporate the notion of equilibrium exchange rate and the relative adjustment process. In both cases, we compute predictions at various time intervals, starting from the very short run (1 month ahead) to the long run (12 months ahead).

The difference model is the nonlinear version of

$$\Delta_k e_t = \alpha + \nabla_k X_t' \gamma + \epsilon_{t+k}, \tag{1}$$

that is,

$$\Delta_k e_t = f(\nabla_k X_t) + \epsilon_{t+k}, \tag{2}$$

The error correction model is the nonlinear version of

$$\Delta_k e_t = \alpha + \beta(e_t - X_t' \bar{\gamma}) + \epsilon_{t+k}, \tag{3}$$

that is,

$$\Delta_k e_t = f(e_t, X_t) + \epsilon_{t+k}. \tag{4}$$

In the equations above, the term X includes different variables that identify different models. In particular, using the symbols m, y, π, and i respectively for log of money, log of output, log of price level, and interest rate, we consider the following models:

- Standard monetary model: $X_t = [\hat{m}_t, \hat{y}_t]$

- Monetary model with sticky prices: $X_t = [\hat{m}_t, \hat{y}_t, \hat{\pi}_t]$

- Monetary model with sticky prices and UIP deviations: $X_t = [\hat{m}_t, \hat{y}_t, \hat{\pi}_t, \hat{i}_t]$

- Taylor rule model: $X_t = [\hat{\tilde{y}}_t, \hat{\pi}_t, \hat{i}_t]$ where $\tilde{y}$ defines the output gap.

In the next section, we follow most of the literature on estimating rolling regressions in advanced economies in the post-Bretton Woods period. The estimation (training) sample is set to 120 observations (10 years), after which out-of-sample forecasts are produced. Then, the sample is rolled forward one period at a time and the procedure repeated until there are no more available observations to forecast. This approach is generally preferred over recursive forecasts[8] as it allows taking into account parameter instability over time.

4.2 Methods

In addition to the standard regression approach, we use ML algorithms, focusing, in particular, on the most widely used techniques. In the following paragraphs, we provide a brief introduction to these techniques. For details, see the excellent monographs by Hastie, Tibshirani, and Friedman (2009) and James et al. (2013).

In implementing alternative approaches, we chose models that share the following features:

1. Flexibility: Exchange rate forecasts may require regression models or classification models depending on whether one is interested in forecasting the magnitude or the direction of change of the exchange rate.

2. Non-linearity: The function mapping the explanatory variables to the response variable may be non-linear.

3. Interactions: Standard exchange rate models generally assume reduced forms, where variables enter additively, whereas more complex models may consider possible interaction effects. For example, the effect of money or interest rate on the exchange rate may depend on the level (or the growth rate) of GDP.

In this study, we use the major ML tools that share the properties mentioned above: regularized regression splines with and without interactions, random forests, and support vector machines.

[8] Here, starting from the test period, the sample is simply extended one period at a time instead of being rolled.

4.2.1 Regularized regression splines

Polynomials are a natural approach to modeling data non-linearity by adding to the linear model power functions of predictors. Regression splines extend this approach and, instead of applying a high-degree polynomial, they fit separate low-degree polynomials over different regions of X.

For example, a piecewise cubic polynomial fits a cubic regression model such as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \epsilon_i, \tag{5}$$

where the coefficients β_0, β_1, β_2, and β_3 are different in different regions of the domain of X. The points separating the regions are called knots. To avoid discontinuities, splines require that around the knots piecewise polynomials be continuous and smooth (and also that their first and second derivatives be continuous). More specifically, we construct splines using a B-spline basis,[9] so that we can apply standard regression techniques using a transformation of the original explanatory variables as regressors.

Regression splines are known to deliver results superior to those by polynomial regression. This is because they introduce local flexibility with the use of knots, while keeping the degree of the polynomial low. On the contrary, simple polynomials need to have a high degree to produce comparably flexible fits.

We estimate two types of spline models: a *cubic spline regression* where individual predictors enter additively[10] and a *cubic spline regression with interactions*, where all the products of the B-spline basis functions appear as regressors.

Given the complexity (i.e., the large number of model degrees of freedom) of these models and their tendency to produce high-variance predictions, we regularize them through elastic net penalization.

Developing flexible and unconstrained forecasting models introduces the bias-variance trade-off problem. Consider a general statistical model $y = f(x) + \epsilon$, for which we need to assess the out-of-sample predictive accuracy using the mean squared error (MSE) as a risk measure. Given an out-of-sample observation x_0 and an estimation sample (which does not include x_0) used to obtain the fitted model $\hat{f}$, it can be shown that MSE can be decomposed as follows:

$$E(y_0 - \hat{f}(x_0))^2 = \mathrm{Var}(\hat{f}(x_0)) + \Big[\mathrm{Bias}(\hat{f}(x_0))\Big]^2 + \mathrm{Var}(\epsilon). \tag{6}$$

[9]See Hastie, Tibshirani, and Friedman (2009), Ch.5 for a detailed explanation.

[10]See the Section on Additive Models in Hastie, Tibshirani, and Friedman (2009)

The $\text{Var}(\hat{f}(x_0))$ term refers to the variance of the f estimator, $\hat{f}$, in a repeated sampling framework; the $\left[\text{Bias}(\hat{f}(x_0))\right]^2$ term denotes the bias of the estimator, that is, the difference between the average prediction of the model and the true value. Equation (6) shows that minimizing the prediction error requires the selection of a model with both a low variance and a low bias. Statistical learning models, being very flexible and allowing for non-linearities, can achieve a low bias but at the cost of a high variance. The solution is to introduce some sort of *regularization*, which reduces the variance at the cost of introducing some small bias. Ridge and Lasso are well known forms of regularization, which work by adding a penalty term to the estimated parameters. Ridge regression regularizes the coefficients by adding an L_2 penalty to the least-squares objective function, whereas Lasso uses a L_1 penalty, which tends to produce a sparse solution by setting some coefficients to zero. In a highly influential paper, Zou and Hastie (2005) introduce the *Elastic Net* penalty showing that it improves both Lasso and Ridge regression.

$$\lambda \sum_{j=1}^{p} (\alpha \beta_i^2 + (1-\alpha)|\beta_j|) \tag{7}$$

where p is the number of estimated coefficients. As $\alpha \to 1$, the penalty collapses to the Ridge penalty whereas as $\alpha \to 0$, it collapses to the Lasso penalty. In our setting, shrinkage estimators have a natural interpretation as, by shrinking coefficients towards 0, they bias the estimated model in the direction of the random walk, the assumed standard benchmark in exchange rate forecasting.

4.2.2 Random Forest

Random forests are derived from regression trees, of which they constitute an evolution and improvement. Regression trees are known in statistical learning for handling complex problems involving interactions and non-linearities. Moreover, the same tool can be used to handle both quantitative responses (regression trees) and qualitative ones (classification trees). Regression trees are constructed by dividing the predictor space into a set of J non-overlapping regions R_j. Subsequently, in each region, the mean response values for the training observations are computed. The selection of the regions (internal nodes) $1, \dots, J$ is determined by minimizing the residual sum of squares (RSS). This is done recursively by considering all possible predictors $X_1, \dots, X_p$ and all the possible cutoff points s and selecting the predictor-cutoff point pair that delivers the greatest reduction in RSS, in other words, we choose the predictor j and cutoff point s that minimize

$$\sum_{i:x_i \in R_1(j,s)} (y_i - \hat{y}_{R_1})^2 + \sum_{i:x_i \in R_2(j,s)} (y_i - \hat{y}_{R_2})^2 \tag{8}$$

where R_1 and R_2 are the two regions of the predictor j space, $\hat{y}_{R_1}$ is the mean response of the training observations in the $R_1(j,s)$ region of predictor j, defined by the cutoff point s; $\hat{y}_{R_2}$ is defined analogously. Subsequently, the process is repeated recursively for each of the remaining predictors.

In complex problems, decision trees are known to grow into large trees suffering from *high variance*. It is also well-known that in the presence of independent sets of observations, each with its own variance, averaging across the all the sets of observations reduces the variance. Random forests constitute an evolution of regression trees, which allows to considerably reduce the variance of the predictions. This is done by bootstrapping training samples to build a number of decision trees. However, when building these trees, every time a split in a tree is considered, instead of considering the full set of predictors as possible candidates for the subsequent splitting choice, only a *random set* of the potential predictor is considered. This allows *decorrelating* the trees, substantially reducing the variance.[11]

4.2.3 Support Vector Machines

Support vector machines (SVMs) are one of the most popularML algorithms due to their efficiency in predictive regression and classification.

An SVM is an algorithm that constructs the hyperplane that maximizes the distance between two classes of observations (for example positive and negative exchange rate changes). When the two classes are linearly separable, an SVM is analogous to a linear optimization problem solvable with standard tools (i.e., Lagrange multipliers). Often, however, linear separation is not possible; in those cases, a useful result from Cortes and Vapnik (1995) shows that it is possible to project the dataset through a kernel function onto a higher dimensional space (i.e., the feature space), where the dataset is linearly separable.

An SVM selects the optimal separating hyperplane in the following way: first, the perpendicular distance between any observation and the given hyperplane is computed.

[11] The simple bootstrap procedure tends to produce highly correlated trees, which, when averaged out, do not contribute to a large reduction in the variance.

Second, the smallest distance from the observation to the hyperplane is identified, which defines the margin, that is, the maximal width of the slab parallel to the hyperplane that has no interior data points. The optimal separating hyperplane maximizes the margin.

More formally, let $\mathbf{x}$ be a p-element vector of variables and let n be the number of training observations. SVM is the classification function (James et al., 2013)

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + \beta_0 \tag{9}$$

where $\mathbf{x}_i$ is the vector of variables in the training set, y_i is a classifier that takes the values $+1$ or -1, formally assigning each observation to one of the two groups, β_0 is a constant that shifts the SVM output, and α_i are parameters that are non-zero only for the support vectors and depend on the tuning parameter for the soft margin classification. Both β_0 and α_i are chosen optimally within the training period. Finally, we choose the kernel function K following the literature, selecting the Radial Kernel:

$$K(x, x_i) = \exp\left(-\gamma \sum^{p} (x - x_i)^2\right) \tag{10}$$

where γ is a parameter chosen to optimize the fit of the model to the sample.

In practice, when a test observation x is far from a training observation x_i, this implies that over the p dimensions, the Euclidean distance $(x - x_i)$ is large, so $\sum^{p}(x - x_i)^2$ is large and $K(x, x_i)$ is extremely small. Therefore, the training observation x_i plays no role in predicting the class for the test observation x. Using the kernel function is computationally very effective since the kernel has to be computed for each possible pair x, x_i, that is, $n(n-1)/2$ pairs.

SVMs have several interesting features, which make them potentially extremely useful for exchange rate forecasting. The two main advantages are the following:

- By construction, an SVM is optimized to discriminate around the decision margin, while attaching no weight to easily classifiable data. This is its main difference from a regression-based approach: the latter weights all observations, and not just those close to the decision margin, making the regression-based approach less effective in classification problems.

- SVMs deal with non-linearity quite naturally through the kernel function without imposing a particular functional form, which could be valuable in cases such as ours, since there is no well-established theory providing clearly testable implications. This could help overcome a general problem with non-linear models, which are known to perform well in-sample but fail in out-of-sample forecasting (Teräsvirta, 2006).

4.2.4 Assessing model performance

To assess model performance, we follow the conventional approach in the literature, which focuses on statistical tools.[12] More specifically, we use two approaches. First, we calculate the ratio between the root mean squared error (RMSE) of the model and that of a random walk. A value smaller than 1 indicates the model has a better forecasting performance than that of a random walk. Inference is based on the Diebold and Mariano statistic (Diebold and Mariano, 1995). Although the RMSE criterion is useful for assessing whether models are able to forecast the magnitude of exchange rate movements, an alternative approach would focus on whether models can predict the *direction of change* of the exchange rate. Given the financial asset nature of the exchange rate, the direction of change is a useful signal for designing meaningful and profitable investment strategies. We therefore use the direction of change statistic, which is essentially the percentage of correct directional forecast. A value above 50% represents a better forecasting performance against the null of the Random Walk.

4.3 Data

Our analysis focuses on post-Bretton Woods exchange rates for advanced economies. We use non-seasonally adjusted data, implementing our own seasonal adjustment using only backward information with a lagged MA(12) filter. Seasonal adjustment is implemented for prices, CPI (consumer price index), money, and output (industrial production index). The variables are end-of-period values derived from standard sources (mainly IMF International Financial Statistics (IFS)). All the series have been downloaded from Datastream and cover the period from April 1973 (end of the Bretton Woods agreement) to December 2017. For some countries, the sample is restricted due to data availability; in particular, for Eurozone member countries estimation ends in December 1998. The detailed data sources are as follows (whenever the Datastream code is reported, CC

[12] Given the objective of the study, we do not consider an economic evaluation of exchange rate predictability using, for example, asset allocation approaches as in Della Corte, Sarno, and Tsiakas (2009); Della Corte and Tsiakas (2012); Li, Tsiakas, and Wang (2015).

represents the country code):

- Exchange rates: national currency per US Dollar, Datastream, IMF IFS, (CCI..AE.)
- Money: money stock M1, Datastream, IMF IFS, (code CCM1....A)
- Output: industrial production index, Datastream, IMF IFS (code CCI66...F)
- Interest rate: money market rate, Datastream, IMF IFS (code CC60B..ZF...)
- Prices: Consumer Price Index, Datastream, National Statistical Offices (code CCCONPRCF)

5 Results

5.1 Performance assessment

The first analysis we implement is a standard exercise of performance assessment of the different exchange rate models. Tables 1-24 present the detailed results. Each table assesses the performance of an exchange rate model (1. monetary model, 2. monetary model with sticky prices, 3. monetary model with sticky prices and deviations from UIP, and 4. Taylor rule model). For each model, we produce 1-month and 12-month forecasts using different methods: standard ordinary least squares (REG), elastic net on splines (SPENET), elastic net on splines with interactions (SPENETINT), random forest (RF), SVMs (SVM). More specifically, Tables 1-14 assess performance using RMSE statistics: a value below 1 denotes a model that performs better than the random walk. The P value of the Diebold Mariano test is reported next to each coefficient. Tables 15-24 assess performance based on the direction of change. A value below 0.5 denotes a model that outperforms than the random walk. Additionally, in this case, the P value of the relevant test is reported next to each coefficient. In each case, we implement a model specification with first differences as in equation (1) and one with error correction as in equation (3). The last column of each table reports the estimation method that performs the best for each country.

Overall, the results can be summarized as follows:

First, standard exchange rate models, irrespective of the estimation method, even with ML tools, fail to outperform the random walk in the very short run (1 month ahead). This is true for both the standard forecasts and also for forecasting the direction of change, confirming the unpredictability of asset prices at very short horizons.

Second, the performance of standard regression models improves significantly for long run forecasts. This result confirms not only the general findings in the literature, but also the standard practice of market makers and practitioners who tend to use fundamentals-based models for long run forecasts while relying on technical analysis for the short run (Cheung and Chinn, 2001; Dick and Menkhoff, 2013).

Third, comparing exchange rate models, sticky prices models (with or without deviations from UIP) exhibit the best predictive performance, although the Taylor rule model also performs well in the long run.

Fourth, ML methods consistently outperform standard regression models in forecasting the exchange rate, both in the short and long run. Although in the short run this is not enough to outperform the random walk, in the long run, ML tools are clearly better, irrespective of the model, country, statistic (magnitude or direction of change), or model specification (first difference or ECM). The magnitude of the statistics is worth noticing: the ratio of RMSEs is mostly below 0.5 and often below 0.3, in some cases showing the remarkable predictive abilities of ML tools.

Overall, more flexible tools allowing for non-linearities and interaction effects seem to perform better, especially with more complex models. Finally, there is also a clearly best performer among ML tools: an SVM is by far the best tool among those identified in this paper: it wins in 85% of the cases.

Having established these stylized facts emerging from our dataset, without loss of generality, we proceed by focusing on an SVM as the reference ML tool and on the more general monetary model with sticky prices and UIP deviations as the benchmark model (ECM specification).

5.2 Model and specification comparison

Given the consistent forecasting performance of ML tools, we can exploit them to compare different exchange rate models. Focusing on 12-month forecasts, we use SVMs to compare model performance across specifications.

Figure 1 displays the results for individual countries comparing the difference specification with ECM (currencies). Overall, the ECM specification delivers lower RMSE ratio values than the difference specification, with values consistently below 0.5. Looking at the different exchange rate models, despite some differences across countries, the sticky prices versions of the monetary model seem to be preferable.

Figure 2 provides a more compact representation by showing the mean RMSE of

SVM predictions across different types of models and specifications. In general, sticky price specifications perform better, both with the difference and ECM specification. This is consistent with the fact that, at least in the long run, deviations from PPP and the presence of an equilibrium relationship between exchange rate and fundamentals are relevant for predictive purposes.

5.3 Forecasting horizon

The previous section established that ML methods outperform standard tools in forecasting the exchange rate 12 months ahead but fail to outperform the random walk in 1-month ahead forecasts. The natural question that arises is at which horizon fundamentals contain information that can be used by ML to forecast the exchange rate.

In Figure 3, we show the performance of an SVM at different forecasting horizons. The figure plots the RMSE ratio for each month for 1 to 12 months ahead forecasts. There is a striking similarity across countries. SVM performance improves almost monotonically with the length of the forecasting horizon up to 9-12 months, where it stabilizes. Notice that the SVM model already displays good predictive ability at the 3-month horizon.

We can therefore generalize the results of the previous section: with the exception of the very short run (1-2 months), the ML methods consistently outperform standard forecasting tools, irrespective of the country or horizon considered.

5.4 Forecast consistency across time

The results of the previous section were obtained using the entire forecasting period. However, the literature stresses that the choice of the forecasting horizon matters greatly; there is a substantial change over time in the predictive ability of exchange rate models (Cheung, Chinn, and Pascual, 2005; Giacomini and Rossi, 2010; Rogoff and Stavrakeva, 2008).

To investigate this issue, Figures 4-21 report the results of the Giacomini and Rossi (2010) fluctuation test. The test assesses the time variation in the models" relative forecasting performance by computing the rolling-window local relative RMSE for the model and the random walk benchmark. The test's null hypothesis is that, at each point in time, the two models have the same predictive performance.

The figures show the test statistics and critical values [13] (dotted line). This is done for each country and each forecasting horizon from 1 to 12 months ahead.

The results obtained in the previous sections are strongly confirmed. Starting from 3 months ahead, ML tools are able to produce forecasts that are extremely robust to the choice of forecasting period. This is likely due to their flexibility—one of the major strength of ML techniques—which allows them to maximize their performance in the presence of unstable environments of parameter instability.[14]

5.5 Variables importance

The results so far show that ML algorithm standard exchange rate models do have good predictive power. This means that fundamentals contain information that can be exploited to predict exchange rate movements consistently. The question that arises is whether some variables help to predict future exchange rate movements better than others. In fact, the previous section showed that the best performing model is the monetary model "augmented" by taking into account PPP and UIP deviations. This task is not easy in the context of statistical learning. On the contrary, one of the drawbacks of ML tools is that they are somewhat of a black box, not providing the information economists are accustomed to, such as the standard output from a regression (i.e., coefficients, degree of significance, and goodness of fit).

To analyze variable importance in the SVM context, we start from the more general model used (the monetary model with sticky prices and UIP deviations) in the ECM specification, we perform repeated permutations on each variable, and then calculate the loss, in terms of RMSE, for the model in which the permuted variable is included. The higher the increase in RMSE when including a permuted variable, the more important the variable is.

Tables 25 - 28 display the results, both for the overall sample and for the sample divided in decades. Table 25 also includes an additional set of columns indicating, for the sake of clarity, the ranking of the variables in terms of importance. The tables reveal a strong regularity: across countries, the level of the exchange rate at time t is the most relevant variable, followed by the price differential, money differential, output differential, and interest rate differential. Interestingly, there are differences across decades; for example, in the 1980s, where differences in monetary policies were stronger, money

[13] We set the ratio between the size of the rolling window and the out-of-sample size at 0.4. Critical values are for the one-sided test.

[14] Rossi (2006) shows that parameter instability is a relevant issue in exchange rate prediction.

differentials tend to matter more than in the subsequent decades.

The relevance of the current value of the exchange rate is related to the error correction formulation of the model being estimated. Although the functional form of an SVM is completely flexible and we do not know exactly the specific function that the model is estimating, the aim of the ECM specification is to capture the relevance of a long run relationship between the relevant variables. In this sense, we can interpret the relevance of the current level of the exchange rate as follows: the long run equilibrium value of the exchange rate constrains the forecast values (considering that the forecasts in this case are 12 months ahead). This is also supported by the relevance of the price differentials, which is in line with the importance of deviations from the PPP, another long run equilibrium relationship.

The evidence so far refers to the variable importance in a sample (permutations are implemented in the estimation phase). Figure 22 reports the information for out-of-sample variable importance, where permutations are implemented on the value of the variables used in forecasting (i.e., on each element of the vector X_t). The results confirm the findings presented in Tables 25 - 28.

5.6 Variable interactions

A second way of investigating the functioning of ML methods is by using partial dependence plots. These plots display the marginal relation between each variable and the outcome variable (i.e., how the relationship between each variable x and the outcome changes at different values of x). This could be instructive of the type and form of the relationship between each fundamental and the exchange rate. Figures 23 - 25 display the results, suggesting some interesting insights. First, the non-linearity thatML models capture emerges clearly. Second, within a highly non-linear pattern, it is possible to identify some recurring patterns. There is a negative relationship between Δe_t and e_t, suggesting a form of adjustment in the behavior of the exchange rate. Moreover, the relationship between the interest differential and Δe_t is U-shaped for most countries and in line with UIP (a positive interest differential is positively correlated with an appreciation of the dollar and a negative differential with a depreciation). The relationship between price differentials and the future exchange rate change is generally negative whereas no clear pattern emerges for the money and output differentials.

6 Conclusions

This study uses the most innovative tools recently appearing in the statistical learning literature to assess the ability of standard exchange rate models in predicting the exchange rate in the short and the long run. Our results show that ML tools display remarkable predicting abilities, consistently outperforming the random walk in forecasting the exchange rate at different forecasting horizons, with the exception of the very short term (1-2 months). Apart from the forecasting performance, our study shows that ML can be used to improve our understanding of the relationship between the exchange rate and economic fundamentals. Fundamentals, as contained in standard exchange rate models, do matter for forecasting the exchange rate but the functional form and the estimation method used by the standard literature are too restrictive and do not allow capturing the complexity of the relationship between exchange rate and fundamentals. The tools we have used help us to partially explain these issues, although much work has to be done to improve the understanding of how ML tools work. This is a major issue in the field of artificial intelligence[15]; its solution will certainly reverberate throughout the social sciences as well.

[15] See the DARPA initiative at `https://www.darpa.mil/program/explainable-artificial-intelligence`

References

Athey, Susan. 2018. "The Impact of Machine Learning on Economics." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay K. Agrawal, Joshua Gans, and Avi Goldfarb. University of Chicago Press, Ch.21.

Box, George E. P., Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung. 2015. *Time series analysis : forecasting and control*. Wiley.

Branson, William H. and Dale W. Henderson. 1985. "The specification and influence of asset markets." In *Handbook of International Economics*, *Handbook of International Economics*, vol. 2, edited by R. W. Jones and P. B. Kenen, chap. 15. Elsevier, 749–805.

Cheung, Y.-W. and M.D. Chinn. 2001. "Currency traders and exchange rate dynamics: A survey of the US market." *Journal of International Money and Finance* 20 (4):439–471. Cited By 182.

Cheung, Yin-Wong, Menzie D. Chinn, and Antonio Garcia Pascual. 2005. "Empirical exchange rate models of the nineties: Are any fit to survive?" *Journal of International Money and Finance* 24 (7):1150–1175.

Cheung, Yin-Wong, Menzie D. Chinn, Antonio Garcia Pascual, and Yi Zhang. 2018. "Exchange Rate Prediction Redux: New Models, New Data, New Currencies." NBER Working Papers 23267, National Bureau of Economic Research, Inc.

Colombo, Emilio, Gianfranco Forte, and Roberto Rossignoli. 2018. "Carry trade returns with Support Vector Machines." *International Review of Finance* .

Cortes, Corinna and Vladimir Vapnik. 1995. "Support-Vector Networks." *Machine Learning* 20 (3):273–297.

Della Corte, Pasquale, Lucio Sarno, and Ilias Tsiakas. 2009. "An Economic Evaluation of Empirical Exchange Rate Models." *Review of Financial Studies* 22 (9):3491–3530.

Della Corte, Pasquale and Ilias Tsiakas. 2012. "Statistical and Economic Methods for Evaluating Exchange Rate Predictability." In *Handbook of Exchange Rates*, edited by J. James, L. Sarno, and I.W. Marsh. Hoboken, NJ: Wiley, 221 – 263.

Dick, Christian D. and Lukas Menkhoff. 2013. "Exchange rate expectations of chartists and fundamentalists." *Journal of Economic Dynamics and Control* 37 (7):1362 – 1383.

Diebold, Francis X. and Roberto S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business & Economic Statistics* 13 (3):253–263.

Dornbusch, Rüdiger. 1976. "Expectations and Exchange Rate Dynamics." *Journal of Political Economy* 84 (6):1161–76.

Engel, C. and K. D. West. 2005. "Exchange Rates and Fundamentals." *Journal of Political Economy* 113 (3):485–517.

Fleming, J. Marcus. 1962. "Domestic Financial Policies under Fixed and under Floating Exchange Rates." *IMF Staff Papers* 9 (3):369–380.

Frenkel, Jacob. 1976. "A Monetary Approach To The Exchange Rate: Doctrinal Aspects And Empirical Evidence." *Scandinavian Journal of Economics* 78:200–224.

Giacomini, Raffaella and Barbara Rossi. 2010. "Forecast comparisons in unstable environments." *Journal of Applied Econometrics* 25 (4):595–620.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning*. Springer Verlag.

Holopainen, Markus and Peter Sarlin. 2017. "Toward robust early-warning models: a horse race, ensembles and model uncertainty." *Quantitative Finance* 17 (12):1933–1963.

Huerta, Ramon, Fernando Corbacho, and Charles Elkan. 2013. "Nonlinear support vector machines can systematically identify stocks with high and low future returns." *Algorithmic Finance* 2:45–58.

James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An Introduction to Statistical Learning*. Springer Verlag.

Li, Jiahan, Ilias Tsiakas, and Wei Wang. 2015. "Predicting Exchange Rates Out of Sample: Can Economic Fundamentals Beat the Random Walk?" *Journal of Financial Econometrics* 13 (2):293–341.

MacDonald, Ronald and Ian W. Marsh. 1997. "On Fundamentals And Exchange Rates: A Casselian Perspective." *The Review of Economics and Statistics* 79 (4):655–664.

Mark, Nelson C. 1995. "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability." *American Economic Review* 85 (1):201–218.

Meade, James E. 1951. *The Theory of International Economic Policy, Vol.1. the Balance of Payments*. Oxford University Press.

Meese, Richard A. and Kenneth Rogoff. 1983. "Empirical exchange rate models of the seventies : Do they fit out of sample?" *Journal of International Economics* 14 (1-2):3–24.

Molodtsova, Tanya and David H. Papell. 2009. "Out-of-sample exchange rate predictability with Taylor rule fundamentals." *Journal of International Economics* 77 (2):167–180.

Mundell, Robert A. 1962. "The Appropriate Use of Monetary and Fiscal Policy for Internal and External Stability." *IMF Staff Papers* 9 (1):70–79.

———. 1963. "Capital Mobility and Stabilization Policy under Fixed and Flexible Exchange Rates." *The Canadian Journal of Economics and Political Science* 29 (4):475–485.

Mussa, Michael. 1976. "The Exchange Rate, The Balance Of Payments and Monetary and Fiscal Policy Under A Regime of Controlled Floating." *Scandinavian Journal of Economics* 78:229–48.

Obstfeld, Maurice and Kenneth Rogoff. 2001. "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?" In *NBER Macroeconomics Annual 2000, Volume 15*, NBER Chapters. National Bureau of Economic Research, Inc, 339–412.

Papadimitriou, Theophilos, Periklis Gogas, and Efthimios Stathakis. 2014. "Forecasting energy markets using support vector machines." *Energy Economics* 44 (0):135 – 142.

Rogoff, Kenneth S. and Vania Stavrakeva. 2008. "The Continuing Puzzle of Short Horizon Exchange Rate Forecasting." NBER Working Papers 14071, National Bureau of Economic Research, Inc.

Rossi, Barbara. 2006. "Are Exchange Rates Really Random Walks? Some Evidence Robust To Parameter Instability." *Macroeconomic Dynamics* 10 (01):20–38.

———. 2013. "Exchange Rate Predictability." *Journal of Economic Literature* 51 (4):1063–1119.

Sarno, Lucio, Giorgio Valente, and Hyginus Leon. 2006. "Nonlinearity in Deviations from Uncovered Interest Parity: An Explanation of the Forward Bias Puzzle." *Review of Finance* 10 (3):443–482.

Taylor, Mark, David Peel, and Lucio Sarno. 2001. "Nonlinear Mean-Reversion in Real Exchange Rates: Toward a Solution To the Purchasing Power Parity Puzzles." *International Economic Review* 42:1015–1042.

Teräsvirta, Timo. 2006. "Forecasting economic variables with nonlinear models." In *Handbook of Economic Forecasting*, vol. 1, edited by C.W.J. Granger G. Elliott and A. Timmermann. Elsevier, 413 – 457.

Wilson, Charles A. 1979. "Anticipated Shocks and Exchange Rate Dynamics." *Journal of Political Economy* 87 (3):639–47.

Zou, Hui and Trevor Hastie. 2005. "Regularization and variable selection via the elastic net." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 67 (2):301–320.

Table 1: 1 Month. Monetary model. First difference.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.051	0.999	1.001	0.806	1.001	0.806	1.171	0.988	1.102	0.999	spenet
AT	1.092	0.979	0.984	0.235	0.984	0.235	1.334	0.960	1.129	0.793	spenet
BE	1.057	0.914	0.999	0.463	0.999	0.470	1.239	0.984	1.140	0.936	spenet
CA	1.038	0.958	1.007	0.890	1.007	0.890	1.172	0.998	1.054	0.961	spenet
DK	1.048	0.903	1.004	0.860	1.004	0.860	1.251	0.991	1.038	0.842	spenet
FI	1.051	0.969	1.000	0.535	1.000	0.535	1.284	1.000	1.084	0.977	spenet
FR	1.095	0.955	0.998	0.414	0.998	0.414	1.248	0.956	1.093	0.910	spenet
DE	1.070	0.991	1.011	0.828	1.001	0.547	1.334	0.999	1.174	0.998	spenetint
GR	0.971	0.241	1.000	0.322	1.000	0.322	1.289	0.999	1.031	0.718	reg
IE	1.076	0.984	1.008	0.883	1.008	0.883	1.171	0.981	1.174	0.994	spenet
IT	0.984	0.361	1.003	0.628	1.003	0.614	1.196	0.882	1.020	0.629	reg
JP	1.023	0.893	1.001	0.533	1.001	0.534	1.225	1.000	1.103	1.000	spenet
NL	1.050	0.728	0.990	0.262	0.990	0.262	0.987	0.473	1.079	0.699	rf
NZ	1.009	0.778	1.003	0.779	1.003	0.779	1.113	0.920	1.012	0.679	spenet
NO											NA
PT	0.982	0.391	1.001	0.889	1.001	0.889	0.995	0.485	0.985	0.436	reg
ES	1.047	0.906	1.008	0.920	1.008	0.920	1.206	0.982	1.094	0.929	spenet
SE	1.072	0.999	1.000	0.656	1.000	0.656	1.286	1.000	1.103	1.000	spenet
CH	1.055	0.901	1.000	0.533	1.002	0.743	1.131	0.725	0.989	0.473	svm
GB	1.044	0.899	1.000	0.482	1.000	0.483	1.397	1.000	1.073	0.958	spenet

Table 2: 1 Month. Monetary model. ECM.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.058	0.989	1.002	0.872	1.002	0.872	1.183	1.000	1.075	0.988	spenet
AT	1.083	0.859	0.992	0.088	0.992	0.082	1.068	0.712	1.007	0.528	spenetint
BE	1.166	0.996	1.002	0.588	1.007	0.710	1.110	0.939	1.148	0.965	spenet
CA	1.059	0.991	1.005	0.887	1.005	0.887	1.205	0.996	1.117	1.000	spenet
DK	1.052	0.877	1.002	0.670	1.260	0.999	1.148	0.990	1.095	0.982	spenet
FI	1.033	0.902	1.001	0.620	1.001	0.621	1.137	0.984	1.086	0.960	spenet
FR	1.074	0.915	1.001	0.568	1.001	0.568	1.152	0.972	1.071	0.890	spenet
DE	1.201	1.000	1.027	0.927	1.054	0.997	1.183	0.990	1.038	0.745	spenet
GR	1.005	0.540	0.986	0.107	0.985	0.084	1.298	0.996	0.969	0.279	svm
IE	1.177	0.996	1.007	0.853	1.007	0.869	1.241	0.998	1.090	0.950	spenet
IT	1.103	0.962	1.002	0.857	0.999	0.377	1.197	0.982	1.044	0.771	spenetint
JP	1.064	0.980	0.996	0.218	0.996	0.218	1.180	0.993	1.095	0.999	spenet
NL	1.030	0.637	0.994	0.053	0.994	0.053	1.358	0.974	1.065	0.711	spenet
NZ	1.050	0.873	1.000	0.375	1.000	0.375	1.178	0.990	0.952	0.162	svm
NO											NA
PT	1.050	0.859	1.004	0.808	0.987	0.224	1.201	0.994	1.086	0.974	spenetint
ES	1.102	0.975	1.019	0.952	1.019	0.952	1.285	0.999	1.111	0.984	spenet
SE	1.113	1.000	1.008	0.963	1.008	0.963	1.149	0.996	1.058	0.935	spenet
CH	1.055	0.856	1.000	0.542	1.001	0.704	1.086	0.891	1.165	0.962	spenet
GB	1.089	0.991	1.001	0.778	1.001	0.851	1.137	0.992	1.124	0.993	spenetint

Table 3: 1 Month. Monetary model, sticky prices. First difference.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.06	0.994	1.00	0.806	1.00	0.806	1.11	0.986	1.14	1.000	spenet
AT	1.14	0.988	0.98	0.148	0.98	0.148	1.19	0.887	1.14	0.791	spenet
BE	1.08	0.910	1.01	0.657	1.01	0.644	1.17	0.940	1.13	0.875	spenetint
CA	1.04	0.962	1.01	0.946	1.01	0.946	1.14	0.999	1.10	0.999	spenet
DK	1.07	0.968	1.00	0.833	1.00	0.833	1.13	0.963	1.14	1.000	spenet
FI	1.05	0.911	1.00	0.612	1.00	0.612	1.15	0.998	1.16	1.000	spenet
FR	1.10	0.934	1.00	0.550	1.00	0.499	1.15	0.906	1.13	0.960	spenetint
DE	1.08	0.995	1.01	0.792	1.01	0.810	1.15	0.974	1.15	0.993	spenet
GR	0.97	0.245	1.00	0.322	1.00	0.322	1.18	0.996	1.01	0.529	reg
IE	1.11	0.989	1.00	0.842	1.00	0.881	1.18	0.993	1.16	0.988	spenet
IT	1.00	0.523	1.00	0.836	1.00	0.880	1.14	0.881	1.08	0.860	re
JP	1.03	0.907	1.00	0.478	1.00	0.478	1.14	0.999	1.11	0.998	spenetint
NL	1.09	0.897	0.98	0.140	0.98	0.140	1.06	0.687	1.08	0.680	spenet
NZ	1.02	0.679	1.00	0.530	1.00	0.530	1.01	0.549	1.06	0.947	spenetint
NO											
PT	1.03	0.722	1.00	0.838	1.00	0.838	1.01	0.546	1.03	0.634	spenet
ES	1.06	0.951	1.01	0.901	1.01	0.901	1.15	0.969	1.11	0.969	spenet
SE	1.10	0.995	1.00	0.797	1.00	0.797	1.23	1.000	1.13	1.000	spenet
CH	1.07	0.771	1.00	0.709	1.00	0.805	0.97	0.423	1.15	0.754	rf
GB	1.06	0.972	1.00	0.866	1.00	0.866	1.24	1.000	1.08	0.976	spenet

Table 4: 1 Month. Monetary model sticky prices. ECM.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.077	0.984	1.004	0.793	1.004	0.793	1.187	1.000	1.056	0.944	spenet
AT	1.104	0.873	0.992	0.088	0.992	0.082	1.012	0.542	1.004	0.515	spenetint
BE	1.228	0.996	1.002	0.588	1.354	0.993	1.141	0.980	1.147	0.964	spenet
CA	1.057	0.977	1.006	0.811	1.006	0.811	1.166	0.992	1.083	0.995	spenet
DK	1.034	0.714	1.003	0.791	1.260	0.992	1.080	0.929	1.077	0.923	spenet
FI	1.063	0.993	1.002	0.689	1.002	0.704	1.132	0.986	1.069	0.917	spenet
FR	1.075	0.949	1.001	0.568	1.001	0.568	1.200	0.998	1.060	0.845	spenet
DE	1.292	1.000	1.015	0.942	1.082	0.944	1.172	0.988	1.031	0.706	spenet
GR	1.028	0.759	0.968	0.053	1.006	0.569	1.324	0.998	0.983	0.375	spenet
IE	1.161	0.998	1.007	0.887	1.151	0.990	1.182	0.987	1.083	0.944	spenet
IT	1.025	0.674	1.098	0.966	1.061	0.923	1.148	0.909	1.068	0.847	reg
JP	1.093	0.998	0.996	0.339	0.996	0.339	1.143	0.977	1.101	0.999	spenet
NL	1.032	0.631	0.994	0.053	0.994	0.053	1.332	0.977	0.998	0.493	spenet
NZ	1.071	0.910	0.999	0.354	0.999	0.354	1.161	0.978	0.938	0.109	svm
NO											NA
PT	1.082	0.959	0.994	0.271	0.990	0.243	1.206	0.981	1.102	0.994	spenetint
ES	1.034	0.753	1.019	0.952	1.019	0.952	1.244	0.995	1.084	0.949	spenet
SE	1.145	1.000	1.008	0.958	1.008	0.958	1.144	0.993	1.074	0.973	spenetint
CH	1.048	0.766	1.100	0.915	0.999	0.167	1.127	0.914	1.244	0.988	spenetint
GB	1.115	0.995	1.002	0.806	1.001	0.892	1.128	0.994	1.113	0.996	

Table 5: 1 Month. Monetary model sticky prices, uip deviations. First differences.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.070	0.996	1.007	0.872	1.007	0.872	1.130	0.996	1.135	1.000	spenet
AT	1.142	0.990	0.984	0.148	0.984	0.148	1.254	0.956	1.184	0.883	spenet
BE	1.081	0.918	1.010	0.685	1.010	0.689	1.167	0.926	1.099	0.811	spenetint
CA	1.037	0.935	1.010	0.861	1.010	0.861	1.106	0.997	1.104	0.996	spenet
DK	1.031	0.669	1.000		1.000		1.282	0.979	1.218	0.986	spenet
FI	1.097	0.986	1.007	0.791	1.009	0.824	1.218	0.999	1.257	1.000	spenet
FR	1.204	0.929	1.001	0.534	1.000	0.512	1.112	0.827	1.111	0.933	spenetint
DE	1.075	0.991	1.010	0.797	1.008	0.754	1.095	0.945	1.129	0.992	spenetint
GR											NA
IE	1.240	0.942	1.004	0.975	1.017	0.940	1.198	0.995	1.157	0.995	spenet
IT	1.020	0.628	1.005	0.837	1.005	0.881	1.064	0.752	1.135	0.971	spenetint
JP	1.035	0.922	1.002	0.560	1.002	0.560	1.080	0.983	1.132	1.000	spenet
NL	1.182	0.983	0.984	0.141	0.984	0.141	1.144	0.868	1.138	0.815	spenet
NZ	1.018	0.684	1.002	0.596	1.002	0.599	1.038	0.742	1.070	0.961	spenet
NO											NA
PT	1.038	0.756	1.000	0.498	1.000	0.160	0.964	0.362	1.026	0.592	rf
ES	1.072	0.970	1.006	0.905	1.006	0.905	1.121	0.939	1.154	0.986	spenet
SE	1.236	0.965	1.005	0.902	1.005	0.902	1.200	1.000	1.134	1.000	spenet
CH	1.078	0.799	1.002	0.709	1.004	0.830	0.901	0.224	1.098	0.698	rf
GB	1.067	0.973	1.001	0.866	1.001	0.866	1.184	0.999	1.080	0.961	spenet

Table 6: 1 Month. Monetary model sticky prices, uip deviations. ECM.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.085	0.975	1.004	0.794	1.004	0.800	1.163	0.999	1.048	0.895	spenet
AT	1.116	0.807	0.986	0.173	0.985	0.112	1.064	0.719	1.003	0.509	spenetint
BE	1.263	0.999	1.003	0.579	1.251	0.994	1.254	0.991	1.093	0.850	spenet
CA	1.060	0.936	1.007	0.831	1.007	0.831	1.145	0.981	1.095	0.985	spenet
DK	1.037	0.616	1.001	0.912	1.735	0.999	1.126	0.885	1.173	0.985	spenet
FI	1.024	0.716	0.998	0.423	0.999	0.473	1.089	0.875	1.161	0.962	spenet
FR	1.098	0.884	1.001	0.551	1.001	0.553	1.261	1.000	1.028	0.647	spenet
DE	1.311	1.000	1.015	0.921	1.082	0.942	1.134	0.959	1.061	0.833	spenet
GR											NA
IE	1.195	0.994	1.006	0.837	1.005	0.810	1.149	0.965	1.064	0.902	spenetint
IT	0.968	0.229	1.004	0.844	1.000	0.489	1.128	0.908	1.115	0.843	reg
JP	1.072	0.994	0.996	0.342	0.996	0.345	1.167	0.986	1.105	0.999	spenet
NL	1.097	0.686	0.986	0.095	0.995	0.018	1.199	0.911	1.012	0.537	spenet
NZ	1.101	0.945	0.999	0.354	0.999	0.354	1.131	0.945	0.971	0.313	svm
NO											NA
PT	0.989	0.434	0.999	0.257	1.015	0.742	1.221	0.924	1.109	0.908	reg
ES	1.044	0.817	1.023	0.986	1.023	0.986	1.246	0.997	1.081	0.927	spenet
SE	1.142	0.997	1.009	0.960	1.009	0.959	1.118	0.978	1.069	0.960	spenetint
CH	1.083	0.719	1.010	0.671	1.001	0.827	1.111	0.880	1.277	0.994	spenetint
GB	1.150	0.999	1.000	0.568	0.997	0.195	1.128	0.996	1.060	0.933	spenetint

Table 7: 1 Month. Taylor rule model. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.073	0.993	1.003	0.783	1.003	0.783	1.090	0.980	1.039	0.881	spenet
AT	1.155	1.000	1.004	0.687	1.004	0.732	1.073	0.908	1.070	0.912	spenet
BE	1.081	0.918	1.011	0.875	1.004	0.723	1.066	0.870	1.060	0.879	spenetint
CA	1.146	0.999	1.007	0.926	1.007	0.926	1.158	0.987	1.156	1.000	spenet
DK	1.149	0.999	1.005	0.850	1.005	0.850	1.083	0.928	1.058	0.889	spenet
FI	1.159	0.999	1.000	0.460	1.000	0.487	1.082	0.831	1.133	0.961	spenet
FR	1.093	0.963	1.007	0.839	1.007	0.843	1.112	0.964	1.068	0.891	spenet
DE	1.176	0.999	1.010	0.851	1.003	0.634	1.104	0.961	1.108	0.984	spenetint
GR											NA
IE	1.182	0.974	1.000	0.219	1.000	0.219	1.056	0.803	1.082	0.910	spenet
IT	1.057	0.802	1.000	0.501	1.000	0.501	1.046	0.753	1.034	0.717	spenet
JP	1.094	0.999	1.000	0.504	0.999	0.475	1.063	0.930	1.112	0.998	spenetint
NL	1.123	0.987	1.011	0.875	1.010	0.898	1.065	0.893	1.078	0.936	spenetint
NZ	1.117	0.907	1.002	0.832	1.002	0.832	1.152	0.981	1.082	0.947	spenet
NO											NA
PT	1.124	0.912	1.001	0.698	1.001	0.698	1.092	0.821	1.113	0.915	spenet
ES	1.046	0.851	1.004	0.834	1.004	0.834	1.124	0.956	1.073	0.904	spenet
SE	1.234	1.000	1.003	0.860	1.003	0.860	1.091	0.975	1.100	0.999	spenet
CH	1.828	0.999	1.000		1.000		1.106	0.862	1.476	0.998	spenet
GB	1.125	0.999	1.002	0.652	1.002	0.652	1.103	0.983	1.136	1.000	spenet

Table 8: 12 months. Monetary model. First difference.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.924	0.117	0.887	0.014	0.829	0.003	0.804	0.003	0.779	0.001	svm
AT	0.714	0.004	1.679	1.000	0.859	0.308	0.779	0.163	0.459	0.004	svm
BE	1.438	1.000	1.074	0.703	1.284	0.949	1.349	0.954	0.759	0.017	svm
CA	1.075	0.976	1.033	0.963	1.043	0.982	0.899	0.013	0.793	0.000	svm
DK	0.978	0.375	0.953	0.150	0.905	0.050	0.840	0.007	0.619	0.000	svm
FI	1.100	0.920	1.020	0.919	1.010	0.596	0.991	0.437	0.958	0.310	svm
FR	1.011	0.535	0.941	0.097	0.807	0.010	0.679	0.000	0.398	0.000	svm
DE	1.505	1.000	1.133	0.999	1.090	0.939	1.173	0.973	0.767	0.005	svm
GR	0.632	0.010	0.591	0.000	0.606	0.000	0.681	0.011	0.487	0.000	svm
IE	1.619	1.000	1.305	1.000	1.336	0.999	1.483	1.000	1.632	1.000	spenet
IT	0.955	0.221	0.955	0.000	0.891	0.002	0.983	0.418	0.848	0.081	svm
JP	0.883	0.000	0.911	0.000	0.720	0.000	0.775	0.000	0.689	0.000	svm
NL	0.969	0.399	0.499	0.007	1.300	0.815	0.848	0.246	0.421	0.001	svm
NZ	0.926	0.140	0.787	0.002	0.723	0.001	0.807	0.018	0.737	0.013	spenetint
NO											NA
PT	0.904	0.209	0.924	0.000	0.823	0.134	0.642	0.014	0.755	0.121	rf
ES	1.508	1.000	1.302	1.000	1.277	1.000	1.239	0.981	1.073	0.727	svm
SE	1.137	0.998	1.069	0.994	1.084	0.986	0.986	0.418	1.005	0.525	rf
CH	0.401	0.034	0.768	0.003	1.018	0.554	0.597	0.003	0.304	0.008	svm
GB	1.036	0.666	0.908	0.032	0.837	0.009	0.825	0.000	0.843	0.004	rf

Table 9: 2 Months. Monetary model. ECM.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.791	0.000	0.778	0.000	0.678	0.000	0.623	0.000	0.353	0.000	svm
AT	0.597	0.000	0.736	0.056	0.345	0.000	0.540	0.000	0.198	0.000	svm
BE	1.063	0.706	0.538	0.000	0.302	0.000	0.498	0.000	0.195	0.000	svm
CA	0.923	0.086	0.978	0.292	0.905	0.007	0.590	0.000	0.337	0.000	svm
DK	0.841	0.066	0.537	0.000	0.285	0.000	0.565	0.000	0.240	0.000	svm
FI	0.749	0.000	0.711	0.003	0.542	0.000	0.443	0.000	0.330	0.000	svm
FR	0.647	0.000	0.590	0.000	0.359	0.000	0.465	0.000	0.316	0.000	svm
DE	1.296	0.999	0.755	0.020	0.359	0.000	0.487	0.000	0.162	0.000	svm
GR	0.604	0.001	0.721	0.000	0.721	0.000	0.544	0.000	0.290	0.000	svm
IE	1.521	1.000	1.261	0.978	0.526	0.001	0.701	0.000	0.298	0.000	svm
IT	1.089	0.826	0.492	0.001	0.547	0.015	0.551	0.000	0.319	0.000	svm
JP	0.920	0.093	0.607	0.000	0.355	0.000	0.434	0.000	0.229	0.000	svm
NL	0.529	0.000	1.025	0.562	0.659	0.015	0.508	0.000	0.234	0.000	svm
NZ	0.925	0.228	0.385	0.000	0.469	0.000	0.487	0.000	0.268	0.000	svm
NO											NA
PT	0.791	0.028	0.701	0.000	0.721	0.000	0.604	0.000	0.367	0.000	svm
ES	1.247	0.995	1.081	0.861	1.097	0.915	1.026	0.591	0.555	0.000	svm
SE	1.121	0.975	0.892	0.029	0.834	0.000	0.646	0.000	0.279	0.000	svm
CH	0.864	0.164	1.071	0.820	0.368	0.000	0.613	0.014	0.245	0.000	svm
GB	1.000	0.496	0.798	0.007	0.586	0.000	0.570	0.000	0.434	0.000	svm

Table 10: 12 Months. Monetary model, sticky prices. First difference.

	REG Coef.	P Val	SPENET Coef.	P Val	SPENETINT Coef.	P Val	RF Coef.	P Val	SVM Coef.	P Val	Best Model
AU	0.90	0.092	0.83	0.005	0.81	0.001	0.75	0.000	0.63	0.000	svm
AT	1.04	0.608	1.06	0.578	0.87	0.325	0.75	0.115	0.23	0.000	svm
BE	1.87	1.000	1.01	0.521	0.80	0.098	0.84	0.101	0.41	0.000	svm
CA	0.99	0.432	1.04	0.927	1.04	0.913	0.88	0.009	0.68	0.000	svm
DK	1.01	0.544	1.00	0.513	0.85	0.091	0.85	0.015	0.51	0.000	svm
FI	1.13	0.970	0.96	0.104	0.90	0.099	0.85	0.001	0.81	0.011	svm
FR	1.12	0.878	1.00	0.498	0.67	0.005	0.88	0.047	0.52	0.000	svm
DE	1.35	1.000	0.89	0.026	0.80	0.007	0.88	0.006	0.34	0.000	svm
GR	0.71	0.047	0.55	0.000	0.50	0.000	0.56	0.002	0.30	0.000	svm
IE	1.46	1.000	1.42	1.000	1.27	0.999	1.23	1.000	0.82	0.039	svm
IT	1.14	0.943	1.21	0.990	1.01	0.547	0.92	0.052	0.62	0.000	svm
JP	0.90	0.007	0.75	0.000	0.66	0.000	0.63	0.000	0.35	0.000	svm
NL	1.48	0.989	1.25	0.772	0.87	0.346	1.03	0.550	0.39	0.000	svm
NZ	0.68	0.000	0.70	0.000	0.58	0.000	0.65	0.000	0.46	0.000	svm
NO											
PT	1.23	0.926	0.88	0.006	0.58	0.014	0.66	0.006	0.28	0.000	svm
ES	1.79	1.000	1.37	1.000	1.35	1.000	1.36	1.000	0.65	0.000	svm
SE	1.14	0.997	1.01	0.626	1.00	0.463	0.86	0.001	0.70	0.000	svm
CH	1.08	0.570	0.88	0.329	1.14	0.623	0.47	0.022	0.63	0.125	rf
GB	1.08	0.839	0.92	0.043	0.81	0.007	0.86	0.000	0.83	0.011	spenetint

Table 11: 12 Months. Monetary model sticky prices. ECM.

	REG Coef.	P Val	SPENET Coef.	P Val	SPENETINT Coef.	P Val	RF Coef.	P Val	SVM Coef.	P Val	Best Model
AU	0.757	0.000	0.654	0.000	0.692	0.000	0.590	0.000	0.324	0.000	svm
AT	0.502	0.000	0.401	0.000	0.392	0.000	0.516	0.000	0.186	0.000	svm
BE	1.291	0.952	0.402	0.000	0.204	0.000	0.532	0.000	0.191	0.000	svm
CA	0.741	0.000	0.874	0.004	0.625	0.000	0.509	0.000	0.332	0.000	svm
DK	0.745	0.004	0.439	0.000	0.273	0.000	0.573	0.000	0.244	0.000	svm
FI	0.639	0.000	0.454	0.000	0.405	0.000	0.478	0.000	0.303	0.000	svm
FR	0.702	0.000	0.975	0.408	0.639	0.000	0.428	0.000	0.231	0.000	svm
DE	0.991	0.460	0.623	0.001	0.236	0.000	0.394	0.000	0.166	0.000	svm
GR	0.630	0.000	0.721	0.000	0.746	0.000	0.538	0.000	0.191	0.000	svm
IE	1.191	0.941	1.000	0.501	0.447	0.000	0.735	0.001	0.288	0.000	svm
IT	0.910	0.253	0.515	0.007	0.346	0.001	0.577	0.001	0.247	0.000	svm
JP	0.916	0.091	0.462	0.000	0.243	0.000	0.379	0.000	0.204	0.000	svm
NL	0.374	0.000	0.539	0.000	0.416	0.000	0.470	0.000	0.191	0.000	svm
NZ	0.986	0.445	0.552	0.000	0.235	0.000	0.514	0.000	0.263	0.000	spenetint
NO											NA
PT	0.857	0.057	0.701	0.000	0.706	0.000	0.533	0.000	0.194	0.000	svm
ES	0.907	0.164	0.629	0.000	0.814	0.000	0.543	0.000	0.323	0.000	svm
SE	1.127	0.978	0.773	0.001	0.676	0.000	0.592	0.000	0.243	0.000	svm
CH	1.107	0.660	0.883	0.276	0.556	0.061	0.318	0.000	0.351	0.001	rf
GB	0.817	0.010	0.716	0.000	0.646	0.000	0.540	0.000	0.397	0.000	svm

Table 12: 12 Months. Monetary model sticky prices, uip deviations. First differences.

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.937	0.247	0.841	0.017	0.774	0.001	0.743	0.000	0.551	0.000	svm
AT	1.064	0.588	1.238	0.759	0.736	0.176	0.741	0.107	0.249	0.000	svm
BE	2.116	1.000	1.082	0.690	0.899	0.252	0.866	0.138	0.356	0.000	svm
CA	0.924	0.119	1.047	0.942	1.044	0.939	0.825	0.001	0.629	0.000	svm
DK	0.731	0.015	0.545	0.002	0.393	0.002	0.641	0.002	0.328	0.000	svm
FI	0.731	0.014	0.820	0.000	0.535	0.000	0.753	0.000	0.581	0.000	spenetint
FR	1.156	0.901	1.011	0.548	0.649	0.003	0.870	0.039	0.442	0.000	svm
DE	1.436	1.000	0.898	0.036	0.829	0.001	0.866	0.005	0.345	0.000	svm
GR											NA
IE	1.937	0.998	1.459	1.000	1.389	0.939	1.277	1.000	0.905	0.163	svm
IT	0.856	0.113	1.314	0.815	0.777	0.167	0.718	0.011	0.512	0.000	svm
JP	0.752	0.000	0.610	0.000	0.488	0.000	0.577	0.000	0.308	0.000	svm
NL	1.195	0.777	1.372	0.823	0.803	0.263	0.997	0.495	0.399	0.000	svm
NZ	0.637	0.000	0.620	0.000	0.510	0.000	0.644	0.000	0.447	0.000	svm
NO											NA
PT	1.052	0.608	1.272	0.963	0.752	0.150	0.807	0.050	0.325	0.000	svm
ES	1.863	1.000	1.239	1.000	1.320	1.000	1.407	1.000	0.666	0.000	svm
SE	1.170	0.994	1.081	0.918	1.004	0.529	0.924	0.088	0.583	0.000	svm
CH	1.160	0.658	0.810	0.237	0.623	0.107	0.441	0.013	0.434	0.007	svm
GB	1.133	0.887	0.872	0.046	0.766	0.002	0.779	0.000	0.701	0.000	svm

Table 13: 12 Months. Monetary model sticky prices, uip deviations. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.781	0.003	0.631	0.000	0.693	0.000	0.592	0.000	0.357	0.000	svm
AT	0.516	0.000	0.357	0.000	0.350	0.000	0.511	0.000	0.186	0.000	svm
BE	1.597	0.997	0.356	0.000	0.223	0.000	0.568	0.000	0.229	0.000	spenetint
CA	0.715	0.000	0.886	0.003	0.723	0.000	0.512	0.000	0.381	0.000	svm
DK	0.700	0.036	0.692	0.000	0.612	0.000	0.425	0.000	0.162	0.000	svm
FI	0.413	0.000	0.327	0.000	0.182	0.000	0.534	0.000	0.404	0.000	spenetint
FR	0.738	0.002	0.945	0.301	0.572	0.000	0.453	0.000	0.323	0.000	svm
DE	0.926	0.191	0.478	0.000	0.254	0.000	0.418	0.000	0.229	0.000	svm
GR											NA
IE	1.350	0.997	1.170	0.898	1.776	0.755	0.642	0.000	0.496	0.000	svm
IT	0.564	0.006	0.403	0.002	0.296	0.000	0.590	0.002	0.415	0.000	spenetint
JP	0.602	0.000	0.430	0.000	0.238	0.000	0.369	0.000	0.208	0.000	svm
NL	0.352	0.000	0.102	0.000	0.400	0.000	0.445	0.000	0.191	0.000	spenetint
NZ	0.710	0.000	0.436	0.000	0.292	0.000	0.529	0.000	0.263	0.000	svm
NO											NA
PT	0.619	0.000	0.359	0.000	0.209	0.000	0.585	0.000	0.183	0.000	svm
ES	0.865	0.085	1.176	0.997	0.897	0.027	0.592	0.000	0.364	0.000	svm
SE	1.190	0.980	5.321	0.829	51.039	0.839	0.554	0.000	0.329	0.000	svm
CH	1.001	0.501	0.301	0.002	0.851	0.355	0.612	0.026	0.372	0.001	spenetint
GB	0.891	0.087	0.695	0.000	0.441	0.000	0.532	0.000	0.424	0.000	svm

Table 14: 12 Months. Taylor rule model. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.554	0.000	0.761	0.000	0.658	0.000	0.583	0.000	0.452	0.000	svm
AT	0.864	0.090	0.417	0.000	0.273	0.000	0.591	0.000	0.296	0.000	spenetint
BE	0.814	0.010	0.403	0.000	0.377	0.000	0.641	0.000	0.337	0.000	svm
CA	0.885	0.079	0.952	0.108	0.905	0.003	0.582	0.000	0.456	0.000	svm
DK	0.745	0.000	0.766	0.000	0.799	0.000	0.623	0.000	0.489	0.000	svm
FI	0.686	0.003	0.517	0.000	0.308	0.000	0.591	0.000	0.413	0.000	spenetint
FR	0.715	0.000	0.582	0.000	0.612	0.000	0.545	0.000	0.304	0.000	svm
DE	0.901	0.163	0.432	0.000	0.316	0.000	0.571	0.000	0.287	0.000	svm
GR											NA
IE	0.869	0.320	0.443	0.000	0.478	0.000	0.756	0.000	0.521	0.000	spenetint
IT	0.656	0.000	1.011	0.736	1.012	0.761	0.484	0.000	0.348	0.000	svm
JP	0.613	0.000	0.471	0.000	0.309	0.000	0.520	0.000	0.277	0.000	svm
NL	0.744	0.000	0.528	0.000	0.441	0.000	0.588	0.000	0.464	0.000	spenetint
NZ	0.300	0.000	0.154	0.000	0.201	0.000	0.471	0.000	0.324	0.000	spenetint
NO											NA
PT	0.489	0.000	0.218	0.000	0.253	0.000	0.536	0.000	0.270	0.000	spenetint
ES	0.736	0.003	1.204	1.000	1.204	1.000	0.663	0.000	0.277	0.000	svm
SE	0.892	0.059	0.782	0.000	0.782	0.000	0.580	0.000	0.465	0.000	svm
CH	2.495	0.989	1.028	0.532	0.753	0.225	1.157	0.756	0.328	0.002	svm
GB	0.792	0.005	0.763	0.000	0.752	0.000	0.680	0.000	0.446	0.000	svm

Table 15: 1 Month. Sign prediction. Monetary model. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.512	0.698	0.485	0.302	0.485	0.302	0.469	0.127	0.528	0.873	rf
AT	0.514	0.629	0.405	0.162	0.405	0.162	0.405	0.162	0.486	0.500	spenet
BE	0.405	0.065	0.432	0.148	0.432	0.148	0.473	0.364	0.486	0.454	reg
CA	0.514	0.716	0.505	0.603	0.505	0.603	0.503	0.562	0.543	0.957	rf
DK	0.503	0.561	0.491	0.439	0.491	0.439	0.544	0.891	0.533	0.822	spenet
FI	0.537	0.854	0.508	0.618	0.508	0.618	0.525	0.774	0.525	0.774	spenet
FR	0.469	0.307	0.418	0.065	0.490	0.460	0.459	0.240	0.469	0.307	spenet
DE	0.510	0.625	0.478	0.316	0.478	0.316	0.516	0.684	0.529	0.788	spenet
GR	0.515	0.658	0.526	0.729	0.526	0.729	0.567	0.923	0.505	0.580	svm
IE	0.509	0.612	0.464	0.254	0.464	0.254	0.509	0.612	0.500	0.538	spenet
IT	0.411	0.080	0.384	0.030	0.397	0.050	0.411	0.080	0.411	0.080	spenet
JP	0.536	0.932	0.484	0.276	0.484	0.276	0.494	0.421	0.496	0.460	spenet
NL	0.421	0.209	0.421	0.209	0.421	0.209	0.395	0.128	0.474	0.436	rf
NZ	0.483	0.392	0.417	0.041	0.417	0.041	0.417	0.041	0.400	0.018	svm
NO											NA
PT	0.541	0.792	0.527	0.719	0.541	0.792	0.500	0.546	0.486	0.454	svm
ES	0.458	0.146	0.520	0.726	0.514	0.674	0.525	0.774	0.480	0.326	reg
SE	0.519	0.787	0.489	0.346	0.489	0.346	0.491	0.383	0.514	0.724	spenet
CH	0.500	0.581	0.792	0.999	0.792	0.999	0.542	0.729	0.500	0.581	reg
GB	0.448	0.065	0.504	0.578	0.504	0.578	0.509	0.629	0.530	0.838	reg

Table 16: 1 Month. Sign prediction. Monetary model sticky prices. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.450	0.031	0.491	0.378	0.491	0.378	0.491	0.378	0.496	0.459	reg
AT	0.486	0.500	0.405	0.162	0.405	0.162	0.351	0.049	0.378	0.094	rf
BE	0.432	0.148	0.432	0.148	0.432	0.148	0.459	0.281	0.392	0.040	svm
CA	0.514	0.716	0.503	0.562	0.503	0.562	0.527	0.863	0.535	0.920	spenet
DK	0.485	0.379	0.467	0.221	0.467	0.221	0.503	0.561	0.497	0.500	spenet
FI	0.508	0.618	0.531	0.816	0.508	0.618	0.559	0.951	0.525	0.774	reg
FR	0.418	0.065	0.439	0.133	0.490	0.460	0.520	0.693	0.469	0.307	reg
DE	0.516	0.684	0.478	0.316	0.478	0.316	0.452	0.132	0.478	0.316	rf
GR	0.536	0.792	0.505	0.580	0.505	0.580	0.526	0.729	0.443	0.155	svm
IE	0.500	0.538	0.464	0.254	0.464	0.254	0.518	0.682	0.482	0.388	spenet
IT	0.411	0.080	0.521	0.680	0.411	0.080	0.548	0.825	0.438	0.175	reg
JP	0.526	0.863	0.501	0.540	0.491	0.383	0.484	0.276	0.462	0.068	svm
NL	0.421	0.209	0.421	0.209	0.421	0.209	0.474	0.436	0.421	0.209	reg
NZ	0.433	0.085	0.417	0.041	0.417	0.041	0.383	0.007	0.433	0.085	rf
NO											NA
PT	0.419	0.100	0.514	0.636	0.473	0.364	0.554	0.852	0.486	0.454	reg
ES	0.458	0.146	0.508	0.618	0.525	0.774	0.492	0.440	0.435	0.049	svm
SE	0.469	0.116	0.489	0.346	0.489	0.346	0.504	0.579	0.486	0.310	reg
CH	0.458	0.419	0.542	0.729	0.542	0.729	0.583	0.846	0.458	0.419	reg
GB	0.483	0.323	0.500	0.526	0.500	0.526	0.491	0.422	0.504	0.578	reg

Table 17: 1 Month. Sign prediction. Monetary model sticky prices. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.483	0.270	0.514	0.730	0.514	0.730	0.543	0.959	0.493	0.419	reg
AT	0.531	0.716	0.469	0.388	0.469	0.388	0.388	0.076	0.449	0.284	rf
BE	0.488	0.457	0.442	0.166	0.442	0.166	0.407	0.053	0.442	0.166	rf
CA	0.526	0.859	0.500	0.520	0.500	0.520	0.476	0.192	0.490	0.360	rf
DK	0.481	0.328	0.508	0.617	0.525	0.771	0.525	0.771	0.492	0.441	reg
FI	0.475	0.274	0.480	0.326	0.441	0.066	0.497	0.500	0.458	0.146	spenetint
FR	0.464	0.252	0.473	0.317	0.509	0.612	0.564	0.924	0.455	0.195	svm
DE	0.550	0.917	0.533	0.822	0.515	0.678	0.497	0.500	0.467	0.221	svm
GR	0.486	0.424	0.523	0.717	0.486	0.424	0.459	0.222	0.459	0.222	rf
IE	0.476	0.327	0.492	0.464	0.492	0.464	0.492	0.464	0.419	0.044	svm
IT	0.576	0.936	0.541	0.807	0.647	0.998	0.482	0.414	0.482	0.414	rf
JP	0.484	0.276	0.491	0.383	0.504	0.579	0.511	0.690	0.467	0.098	svm
NL	0.540	0.760	0.460	0.336	0.460	0.336	0.460	0.336	0.500	0.556	spenet
NZ	0.500	0.535	0.394	0.009	0.394	0.009	0.402	0.015	0.379	0.003	svm
NO											NA
PT	0.558	0.882	0.535	0.775	0.535	0.775	0.547	0.834	0.547	0.834	spenet
ES	0.435	0.049	0.424	0.025	0.508	0.618	0.463	0.184	0.412	0.012	svm
SE	0.477	0.186	0.514	0.724	0.528	0.884	0.496	0.460	0.467	0.098	svm
CH	0.500	0.566	0.472	0.434	0.472	0.434	0.583	0.879	0.639	0.967	spenet
GB	0.537	0.888	0.500	0.526	0.504	0.576	0.496	0.474	0.508	0.626	rf

Table 18: 1 Month. Sign prediction. Monetary model sticky prices, uip deviations. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.461	0.073	0.518	0.766	0.518	0.766	0.482	0.267	0.480	0.234	reg
AT	0.514	0.629	0.405	0.162	0.405	0.162	0.459	0.371	0.405	0.162	splinenet
BE	0.378	0.024	0.432	0.148	0.392	0.040	0.419	0.100	0.392	0.040	regression
CA	0.497	0.479	0.514	0.716	0.514	0.716	0.519	0.782	0.527	0.863	reg
DK	0.491	0.500	0.544	0.786	0.544	0.786	0.561	0.855	0.526	0.702	reg
FI	0.541	0.831	0.532	0.778	0.532	0.778	0.560	0.910	0.532	0.778	spenet
FR	0.429	0.094	0.469	0.307	0.490	0.460	0.429	0.094	0.408	0.043	svm
DE	0.516	0.684	0.471	0.262	0.497	0.500	0.478	0.316	0.503	0.563	spenet
GR											NA
IE	0.437	0.118	0.495	0.500	0.485	0.422	0.534	0.785	0.476	0.347	reg
IT	0.452	0.241	0.370	0.017	0.384	0.030	0.507	0.592	0.493	0.500	splinenet
JP	0.509	0.654	0.509	0.654	0.509	0.654	0.457	0.046	0.467	0.098	spenet
NL	0.447	0.314	0.421	0.209	0.421	0.209	0.368	0.072	0.474	0.436	rf
NZ	0.433	0.085	0.417	0.041	0.417	0.041	0.450	0.158	0.408	0.027	svm
NO											NA
PT	0.396	0.097	0.458	0.333	0.438	0.235	0.542	0.765	0.542	0.765	reg
ES	0.468	0.236	0.545	0.885	0.519	0.712	0.474	0.288	0.462	0.189	svm
SE	0.464	0.082	0.489	0.346	0.489	0.346	0.479	0.213	0.481	0.243	reg
CH	0.458	0.419	0.542	0.729	0.500	0.581	0.500	0.581	0.500	0.581	reg
GB	0.483	0.323	0.500	0.526	0.500	0.526	0.517	0.723	0.470	0.197	svm

Table 19: 1 Month. Sign prediction. Taylor rule model. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	1.073	0.993	1.003	0.783	1.003	0.783	1.090	0.980	1.039	0.881	spenet
AT	1.155	1.000	1.004	0.687	1.004	0.732	1.073	0.908	1.070	0.912	spenet
BE	1.081	0.918	1.011	0.875	1.004	0.723	1.066	0.870	1.060	0.879	spenetint
CA	1.146	0.999	1.007	0.926	1.007	0.926	1.158	0.987	1.156	1.000	spenet
DK	1.149	0.999	1.005	0.850	1.005	0.850	1.083	0.928	1.058	0.889	spenet
FI	1.159	0.999	1.000	0.460	1.000	0.487	1.082	0.831	1.133	0.961	spenet
FR	1.093	0.963	1.007	0.839	1.007	0.843	1.112	0.964	1.068	0.891	spenet
DE	1.176	0.999	1.010	0.851	1.003	0.634	1.104	0.961	1.108	0.984	spenetint
GR											NA
IE	1.182	0.974	1.000	0.219	1.000	0.219	1.056	0.803	1.082	0.910	spenet
IT	1.057	0.802	1.000	0.501	1.000	0.501	1.046	0.753	1.034	0.717	spenet
JP	1.094	0.999	1.000	0.504	0.999	0.475	1.063	0.930	1.112	0.998	spenetint
NL	1.123	0.987	1.011	0.875	1.010	0.898	1.065	0.893	1.078	0.936	spenetint
NZ	1.117	0.907	1.002	0.832	1.002	0.832	1.152	0.981	1.082	0.947	spenet
NO											NA
PT	1.124	0.912	1.001	0.698	1.001	0.698	1.092	0.821	1.113	0.915	spenet
ES	1.046	0.851	1.004	0.834	1.004	0.834	1.124	0.956	1.073	0.904	spenet
SE	1.234	1.000	1.003	0.860	1.003	0.860	1.091	0.975	1.100	0.999	spenet
CH	1.828	0.999	1.000		1.000		1.106	0.862	1.476	0.998	spenet
GB	1.125	0.999	1.002	0.652	1.002	0.652	1.103	0.983	1.136	1.000	spenet

Table 20: 12 Months. Sign prediction. Monetary model. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.401	0.000	0.407	0.000	0.401	0.000	0.370	0.000	0.320	0.000	svm
AT	0.240	0.007	0.440	0.345	0.440	0.345	0.320	0.054	0.240	0.007	reg
BE	0.565	0.874	0.435	0.187	0.323	0.004	0.403	0.081	0.210	0.000	svm
CA	0.489	0.356	0.545	0.960	0.534	0.907	0.402	0.000	0.363	0.000	svm
DK	0.376	0.001	0.478	0.316	0.382	0.002	0.389	0.003	0.325	0.000	svm
FI	0.479	0.320	0.576	0.979	0.582	0.986	0.412	0.014	0.358	0.000	svm
FR	0.267	0.000	0.384	0.020	0.198	0.000	0.244	0.000	0.221	0.000	spenetint
DE	0.621	0.999	0.593	0.990	0.607	0.996	0.517	0.691	0.338	0.000	svm
GR	0.224	0.000	0.224	0.000	0.224	0.000	0.224	0.000	0.165	0.000	svm
IE	0.480	0.382	0.530	0.758	0.590	0.972	0.550	0.864	0.510	0.618	reg
IT	0.361	0.020	0.213	0.000	0.279	0.000	0.213	0.000	0.230	0.000	spenet
JP	0.361	0.000	0.318	0.000	0.295	0.000	0.275	0.000	0.249	0.000	svm
NL	0.269	0.014	0.885	1.000	0.269	0.014	0.385	0.163	0.192	0.001	svm
NZ	0.361	0.003	0.343	0.001	0.315	0.000	0.324	0.000	0.296	0.000	svm
NO											NA
PT	0.355	0.015	0.484	0.450	0.516	0.648	0.419	0.126	0.403	0.081	reg
ES	0.455	0.138	0.424	0.031	0.430	0.043	0.321	0.000	0.321	0.000	rf
SE	0.389	0.000	0.392	0.000	0.293	0.000	0.295	0.000	0.275	0.000	svm
CH	0.083	0.003	0.083	0.003	0.250	0.073	0.167	0.019	0.167	0.019	reg
GB	0.423	0.013	0.367	0.000	0.364	0.000	0.305	0.000	0.295	0.000	svm

Table 21: 12 Months. Sign prediction. Monetary model sticky prices. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.387	0.000	0.373	0.000	0.348	0.000	0.343	0.000	0.265	0.000	svm
AT	0.440	0.345	0.440	0.345	0.360	0.115	0.360	0.115	0.120	0.000	svm
BE	0.613	0.972	0.371	0.028	0.129	0.000	0.210	0.000	0.145	0.000	spenetint
CA	0.492	0.396	0.578	0.999	0.450	0.032	0.411	0.000	0.291	0.000	svm
DK	0.331	0.000	0.376	0.001	0.382	0.002	0.376	0.001	0.287	0.000	svm
FI	0.461	0.175	0.558	0.940	0.394	0.004	0.333	0.000	0.285	0.000	svm
FR	0.372	0.011	0.256	0.000	0.233	0.000	0.244	0.000	0.233	0.000	spenetint
DE	0.614	0.998	0.455	0.159	0.372	0.001	0.428	0.048	0.172	0.000	svm
GR	0.224	0.000	0.224	0.000	0.165	0.000	0.247	0.000	0.153	0.000	svm
IE	0.610	0.990	0.650	0.999	0.520	0.691	0.540	0.816	0.380	0.010	svm
IT	0.377	0.036	0.246	0.000	0.361	0.020	0.246	0.000	0.197	0.000	svm
JP	0.392	0.000	0.260	0.000	0.244	0.000	0.221	0.000	0.145	0.000	svm
NL	0.462	0.423	0.885	1.000	0.115	0.000	0.500	0.577	0.154	0.000	spenetint
NZ	0.407	0.034	0.370	0.005	0.231	0.000	0.269	0.000	0.204	0.000	svm
NO											NA
PT	0.371	0.028	0.403	0.081	0.290	0.001	0.161	0.000	0.145	0.000	svm
ES	0.461	0.175	0.461	0.175	0.448	0.106	0.370	0.001	0.248	0.000	svm
SE	0.397	0.000	0.542	0.957	0.295	0.000	0.290	0.000	0.221	0.000	svm
CH	0.083	0.003	0.500	0.613	0.583	0.806	0.500	0.613	0.333	0.194	reg
GB	0.395	0.001	0.377	0.000	0.332	0.000	0.327	0.000	0.305	0.000	svm

Table 22: 12 Months. Sign prediction. Monetary model sticky prices. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.326	0.000	0.240	0.000	0.194	0.000	0.213	0.000	0.189	0.000	svm
AT	0.243	0.001	0.027	0.000	0.054	0.000	0.135	0.000	0.054	0.000	spenet
BE	0.378	0.024	0.081	0.000	0.081	0.000	0.216	0.000	0.135	0.000	spenet
CA	0.305	0.000	0.354	0.000	0.173	0.000	0.173	0.000	0.141	0.000	svm
DK	0.296	0.000	0.260	0.000	0.201	0.000	0.225	0.000	0.160	0.000	svm
FI	0.321	0.000	0.139	0.000	0.103	0.000	0.182	0.000	0.121	0.000	spenetint
FR	0.357	0.003	0.235	0.000	0.173	0.000	0.173	0.000	0.163	0.000	svm
DE	0.395	0.005	0.268	0.000	0.268	0.000	0.159	0.000	0.108	0.000	svm
GR	0.392	0.021	0.186	0.000	0.186	0.000	0.155	0.000	0.144	0.000	svm
IE	0.366	0.003	0.366	0.003	0.268	0.000	0.268	0.000	0.179	0.000	svm
IT	0.247	0.000	0.219	0.000	0.205	0.000	0.178	0.000	0.164	0.000	svm
JP	0.321	0.000	0.224	0.000	0.198	0.000	0.122	0.000	0.102	0.000	svm
NL	0.211	0.000	0.237	0.001	0.105	0.000	0.105	0.000	0.053	0.000	svm
NZ	0.492	0.464	0.308	0.000	0.258	0.000	0.125	0.000	0.133	0.000	rf
NO											NA
PT	0.270	0.000	0.135	0.000	0.122	0.000	0.216	0.000	0.095	0.000	svm
ES	0.285	0.000	0.133	0.000	0.139	0.000	0.121	0.000	0.170	0.000	rf
SE	0.354	0.000	0.288	0.000	0.232	0.000	0.221	0.000	0.132	0.000	svm
CH	0.208	0.003	0.167	0.001	0.042	0.000	0.125	0.000	0.167	0.001	spenetint
GB	0.319	0.000	0.319	0.000	0.302	0.000	0.220	0.000	0.172	0.000	svm

Table 23: 12 Months. Sign prediction. Monetary model sticky prices, uip deviations. First difference

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.407	0.000	0.376	0.000	0.373	0.000	0.359	0.000	0.220	0.000	svm
AT	0.400	0.212	0.440	0.345	0.120	0.000	0.320	0.054	0.120	0.000	spenetint
BE	0.581	0.919	0.371	0.028	0.323	0.004	0.226	0.000	0.129	0.000	svm
CA	0.439	0.011	0.556	0.985	0.581	0.999	0.363	0.000	0.243	0.000	svm
DK	0.422	0.186	0.333	0.018	0.400	0.116	0.378	0.068	0.356	0.036	spenet
FI	0.392	0.021	0.237	0.000	0.227	0.000	0.351	0.002	0.216	0.000	svm
FR	0.302	0.000	0.163	0.000	0.186	0.000	0.244	0.000	0.174	0.000	spenet
DE	0.579	0.977	0.455	0.159	0.345	0.000	0.448	0.122	0.131	0.000	svm
GR											NA
IE	0.549	0.853	0.648	0.998	0.484	0.417	0.571	0.929	0.385	0.018	svm
IT	0.475	0.399	0.279	0.000	0.344	0.010	0.230	0.000	0.180	0.000	svm
JP	0.260	0.000	0.219	0.000	0.181	0.000	0.216	0.000	0.107	0.000	svm
NL	0.385	0.163	0.423	0.279	0.154	0.000	0.423	0.279	0.154	0.000	spenetint
NZ	0.361	0.003	0.370	0.005	0.296	0.000	0.287	0.000	0.194	0.000	svm
NO											NA
PT	0.361	0.066	0.417	0.203	0.278	0.006	0.139	0.000	0.139	0.000	rf
ES	0.486	0.401	0.444	0.106	0.472	0.280	0.396	0.008	0.229	0.000	svm
SE	0.410	0.000	0.331	0.000	0.323	0.000	0.298	0.000	0.188	0.000	svm
CH	0.083	0.003	0.500	0.613	0.583	0.806	0.333	0.194	0.167	0.019	reg
GB	0.391	0.001	0.368	0.000	0.350	0.000	0.305	0.000	0.241	0.000	svm

Table 24: 12 Months. Sign prediction. Taylor rule model. ECM

	REG		SPENET		SPENETINT		RF		SVM		Best
	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Coef.	P Val	Model
AU	0.554	0.000	0.761	0.000	0.658	0.000	0.583	0.000	0.452	0.000	svm
AT	0.864	0.090	0.417	0.000	0.273	0.000	0.591	0.000	0.296	0.000	spenetint
BE	0.814	0.010	0.403	0.000	0.377	0.000	0.641	0.000	0.337	0.000	svm
CA	0.885	0.079	0.952	0.108	0.905	0.003	0.582	0.000	0.456	0.000	svm
DK	0.745	0.000	0.766	0.000	0.799	0.000	0.623	0.000	0.489	0.000	svm
FI	0.686	0.003	0.517	0.000	0.308	0.000	0.591	0.000	0.413	0.000	spenet
FR	0.715	0.000	0.582	0.000	0.612	0.000	0.545	0.000	0.304	0.000	svm
DE	0.901	0.163	0.432	0.000	0.316	0.000	0.571	0.000	0.287	0.000	svm
GR											NA
IE	0.869	0.320	0.443	0.000	0.478	0.000	0.756	0.000	0.521	0.000	spenet
IT	0.656	0.000	1.011	0.736	1.012	0.761	0.484	0.000	0.348	0.000	svm
JP	0.613	0.000	0.471	0.000	0.309	0.000	0.520	0.000	0.277	0.000	svm
NL	0.744	0.000	0.528	0.000	0.441	0.000	0.588	0.000	0.464	0.000	spenetint
NZ	0.300	0.000	0.154	0.000	0.201	0.000	0.471	0.000	0.324	0.000	spenet
NO											NA
PT	0.489	0.000	0.218	0.000	0.253	0.000	0.536	0.000	0.270	0.000	spenet
ES	0.736	0.003	1.204	1.000	1.204	1.000	0.663	0.000	0.277	0.000	svm
SE	0.892	0.059	0.782	0.000	0.782	0.000	0.580	0.000	0.465	0.000	svm
CH	2.495	0.989	1.028	0.532	0.753	0.225	1.157	0.756	0.328	0.002	svm
GB	0.792	0.005	0.763	0.000	0.752	0.000	0.680	0.000	0.446	0.000	svm

Figure 1: Model performance comparison. SVM out of sample, rolling estimates

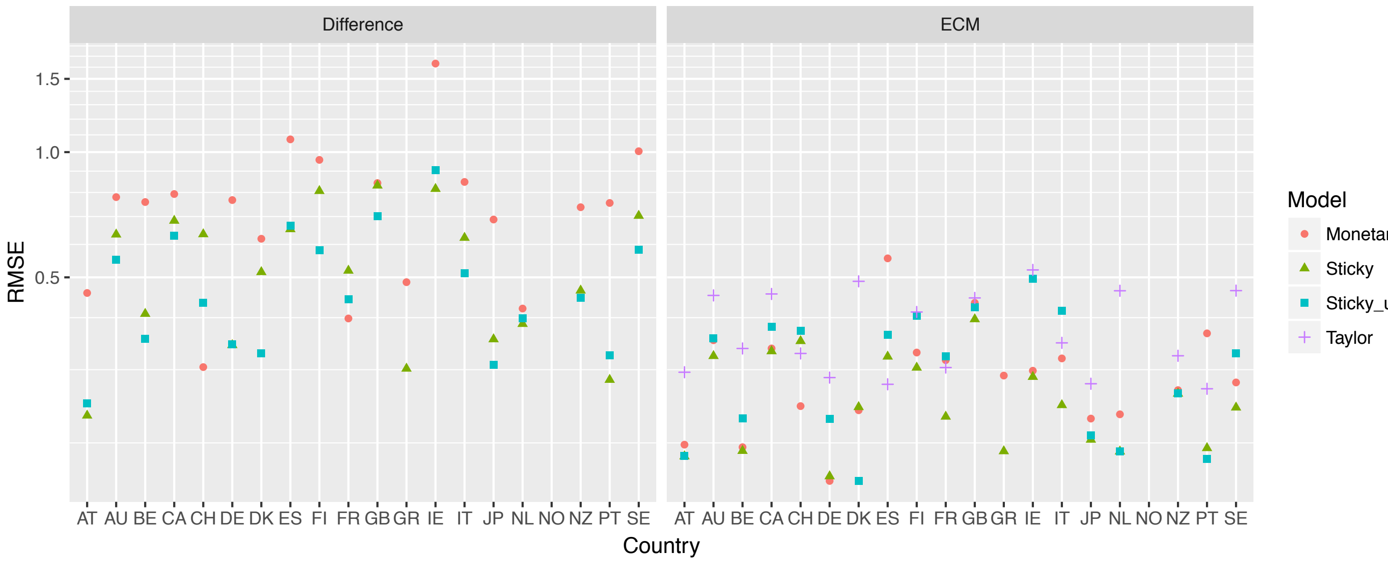

Figure 2: Exchange rate models comparison. SVM out of sample, rolling estimates. Mean RMSE across different currencies.

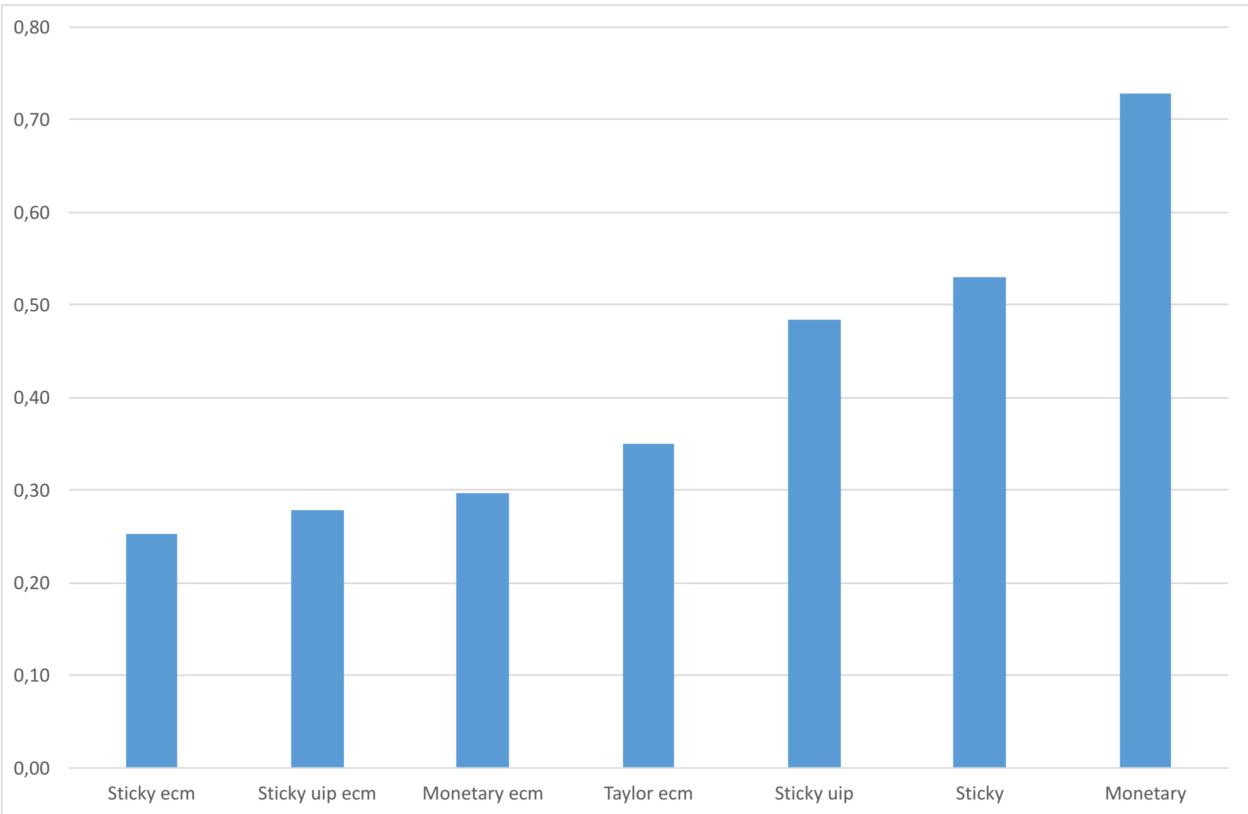

Figure 3: Model performance comparison. Monetary model with sticky prices and UIP deviations, SVM, forecasts at different horizons (1-12 months ahead)

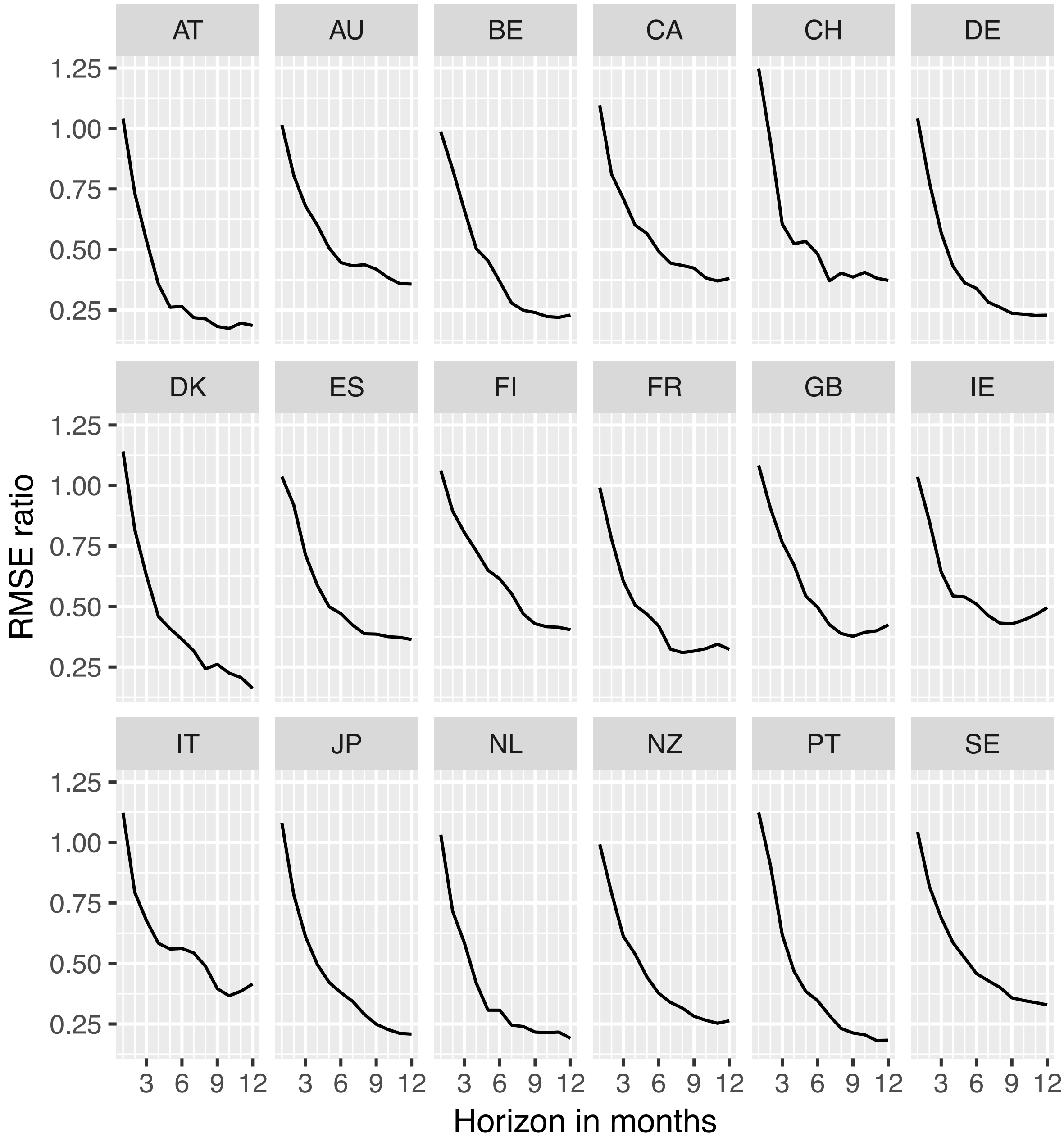

Figure 4: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

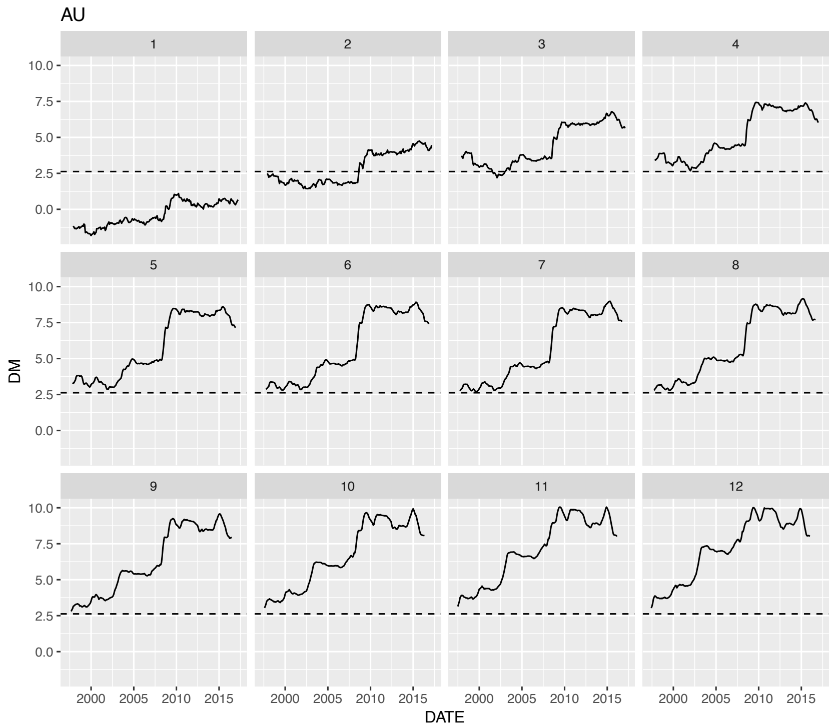

Figure 5: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

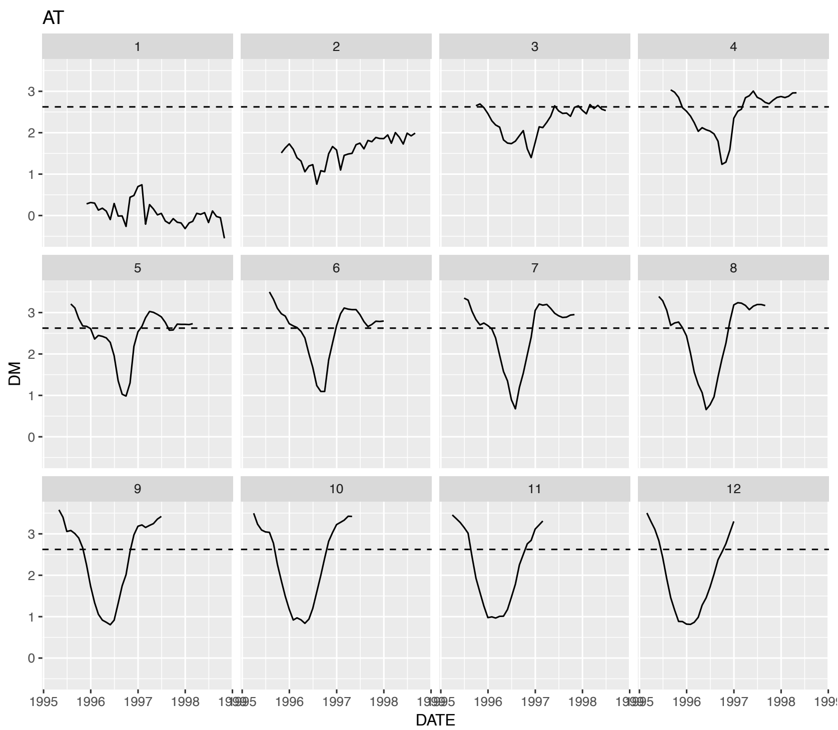

Figure 6: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

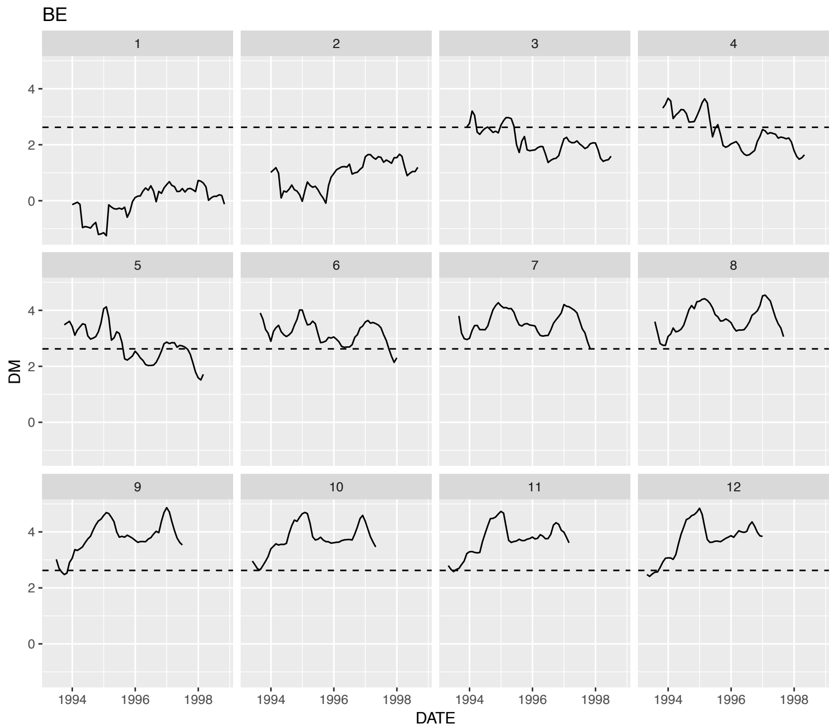

Figure 7: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

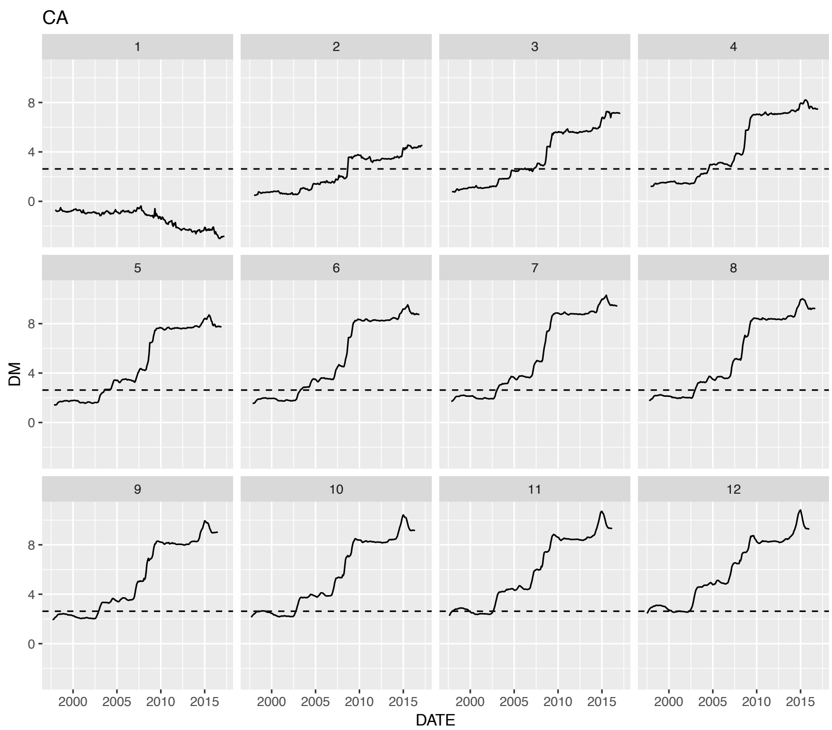

Figure 8: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

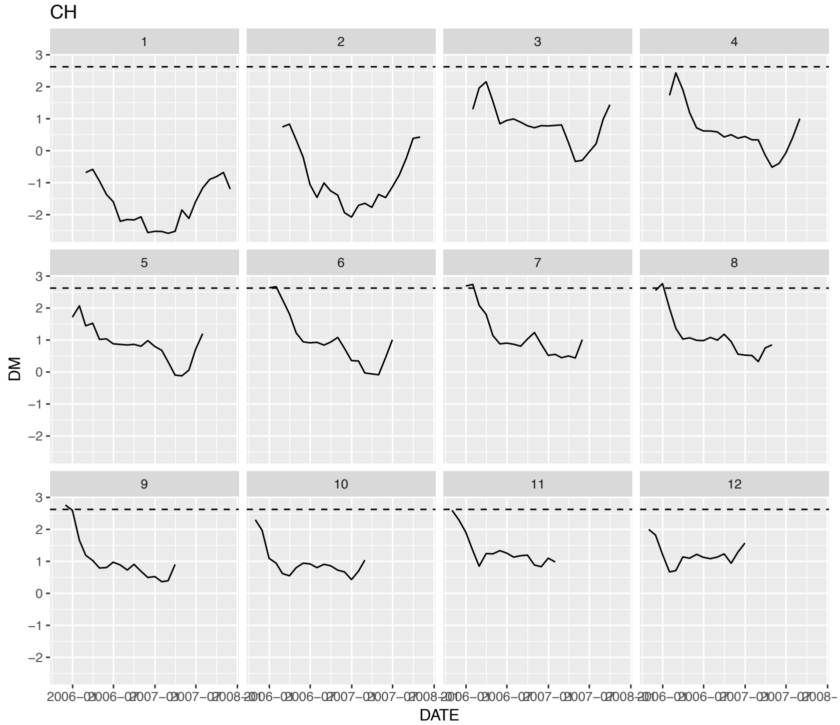

Figure 9: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

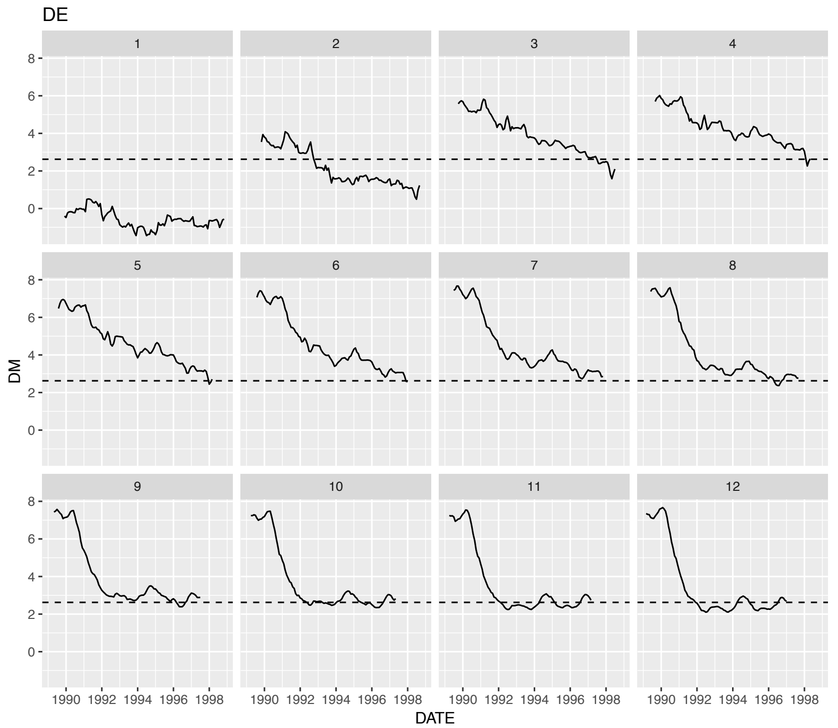

Figure 10: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

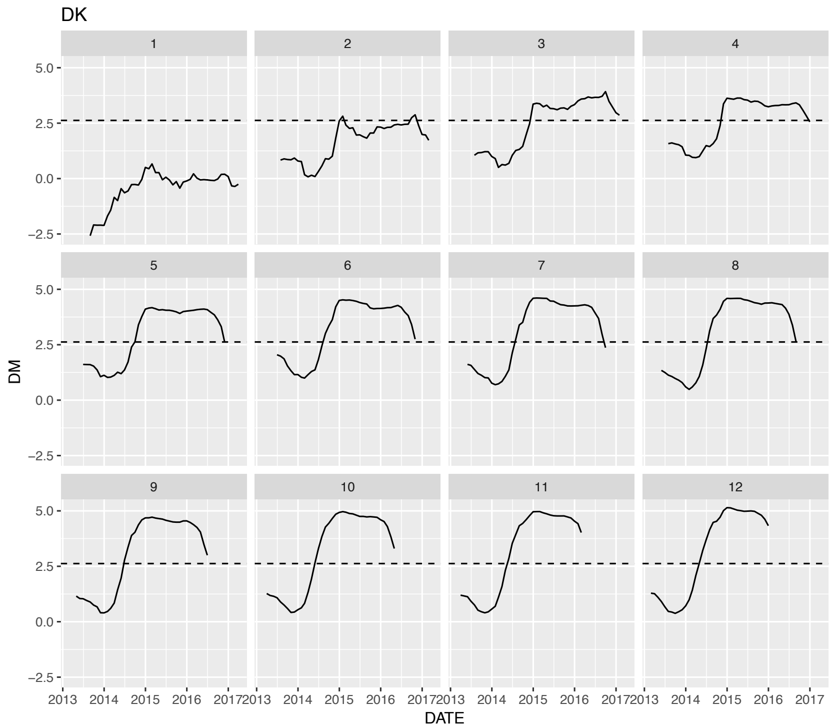

Figure 11: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

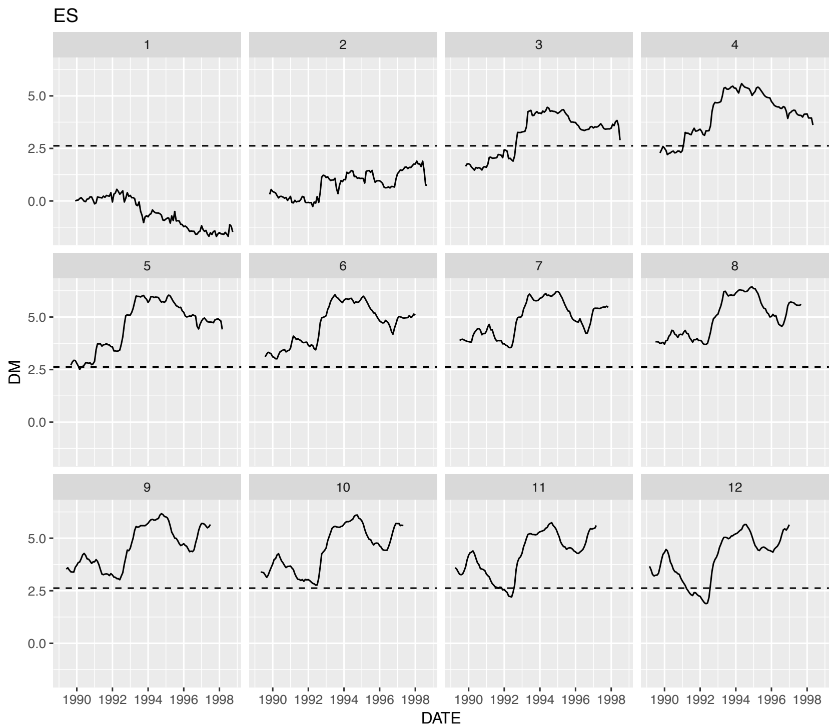

Figure 12: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

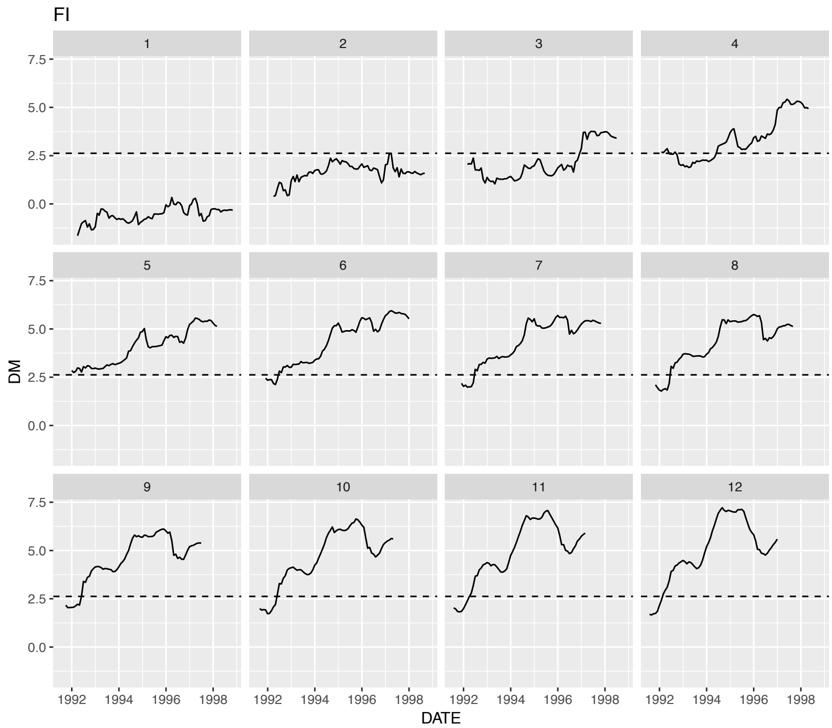

Figure 13: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

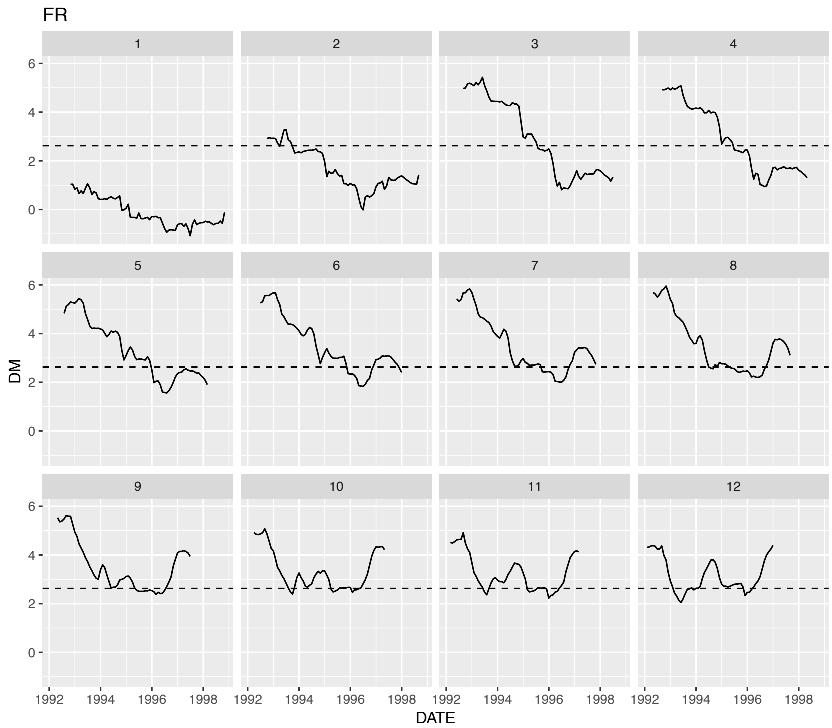

Figure 14: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

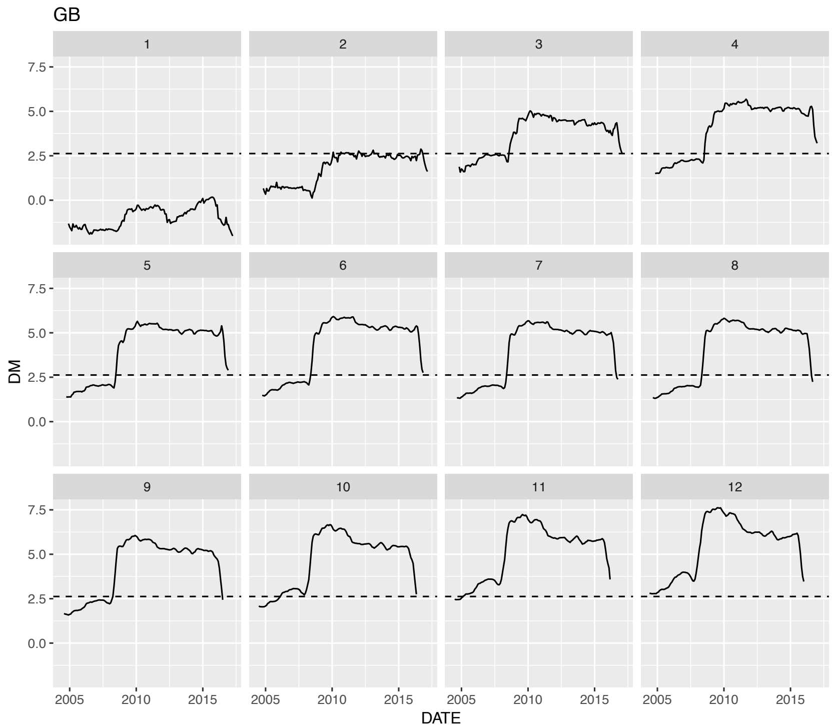

Figure 15: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

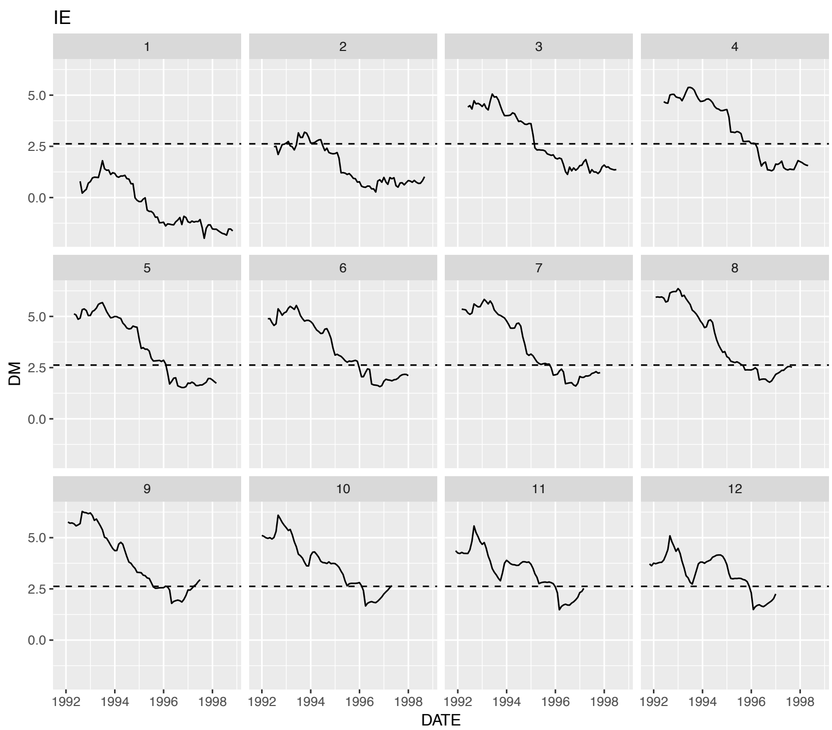

Figure 16: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

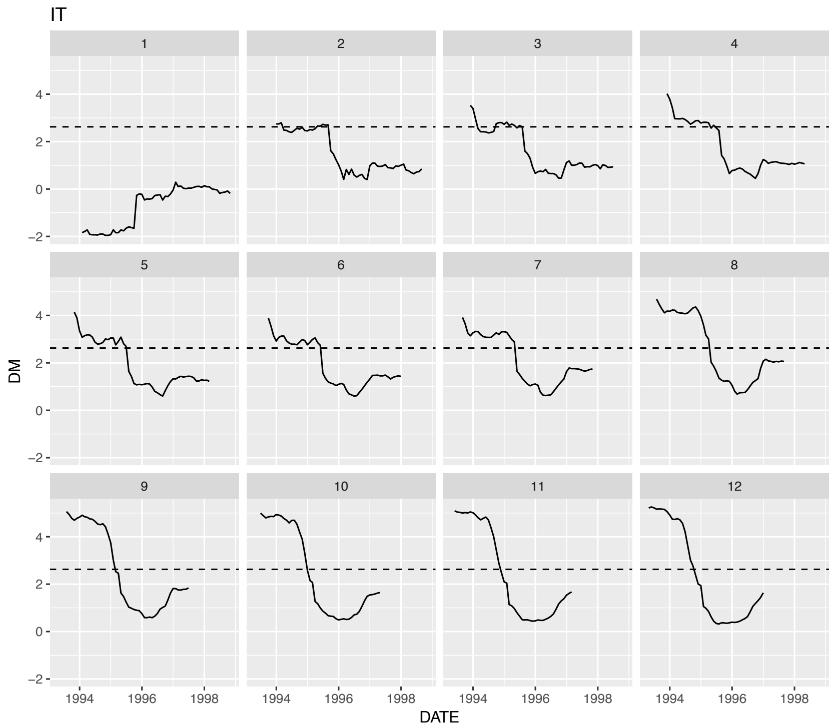

Figure 17: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

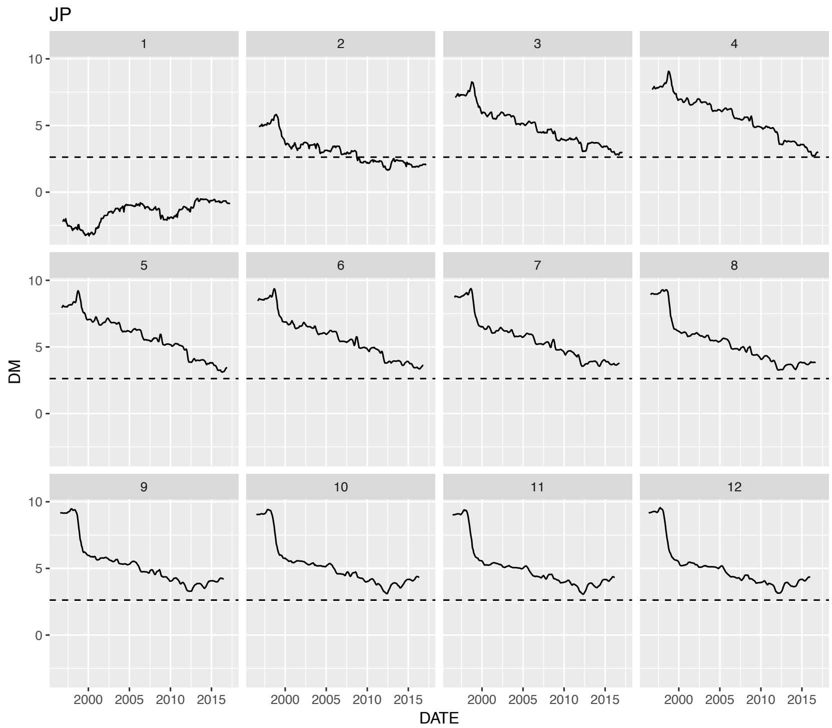

Figure 18: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

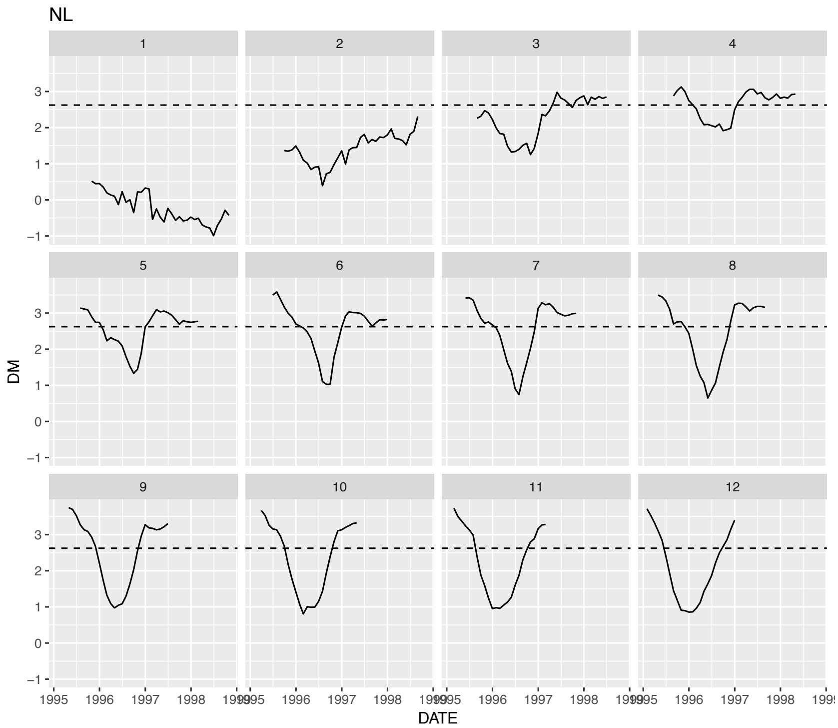

Figure 19: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

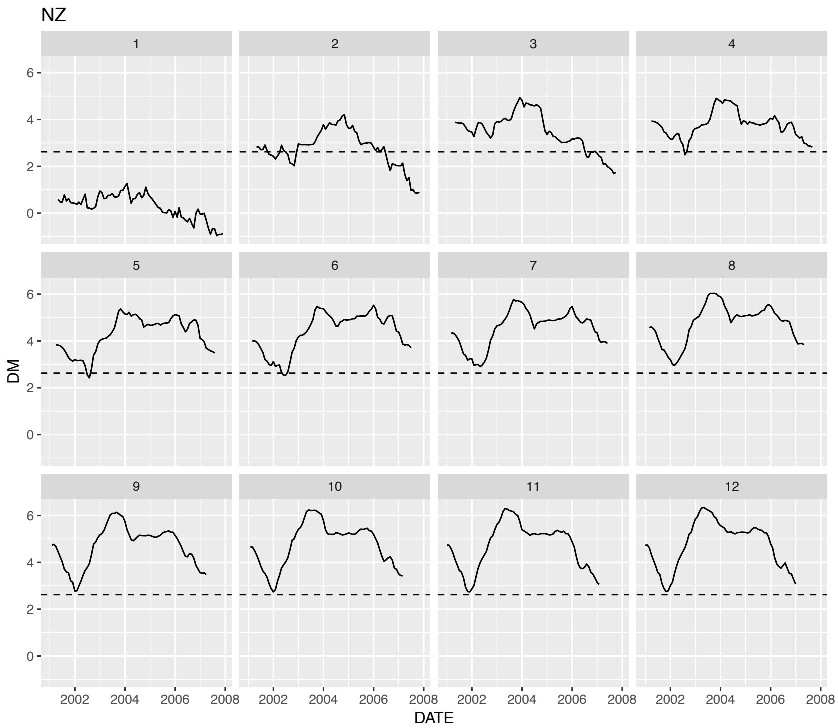

Figure 20: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

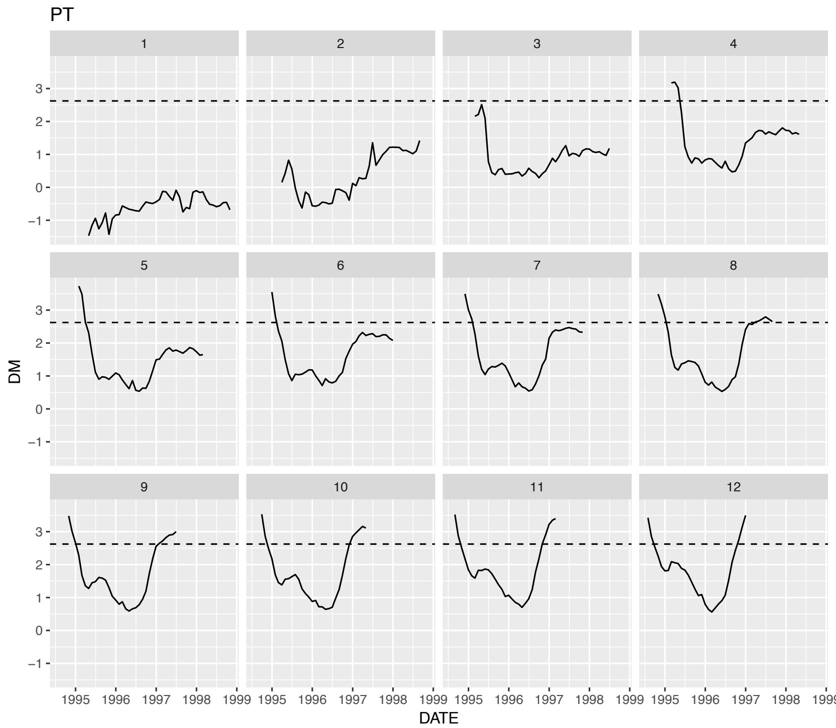

Figure 21: Fluctuation test. Monetary model with sticky prices and UIP deviations, 1 to 12 months ahead forecasts, SVM.

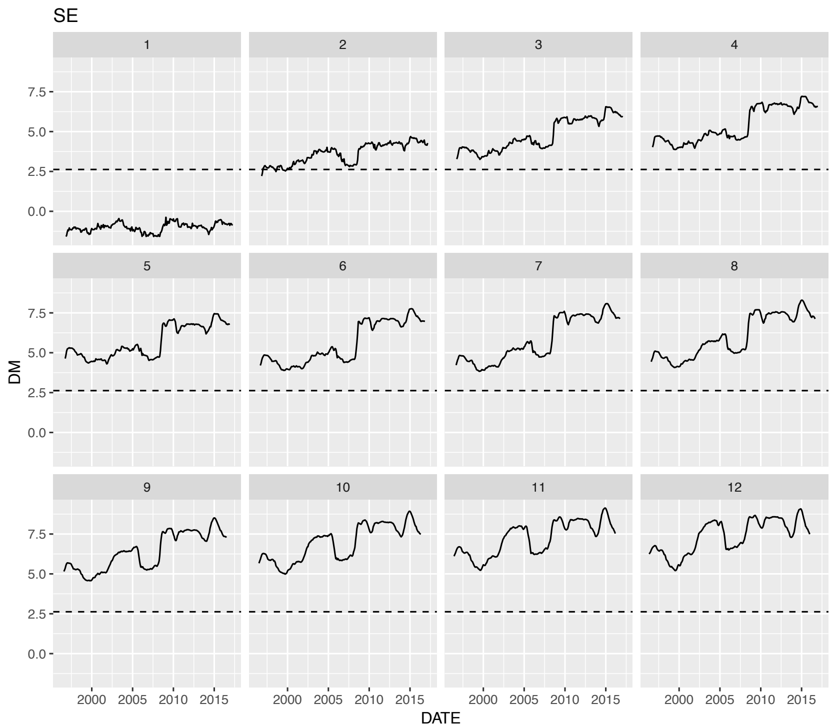

Table 25: Variable importance, overall

Country	m_diff	y_diff	p_diff	i_diff	e	m_diff	y_diff	p_diff	i_diff	e
AU	9.14	9.60	6.18	6.99	13.20	3	2	5	4	1
AT	19.32	17.56	20.44	15.80	27.15	3	4	2	5	1
BE	20.20	14.69	19.17	10.61	21.43	2	4	3	5	1
CA	6.37	7.75	6.26	5.60	7.54	3	1	4	5	2
DK	15.96	16.68	16.31	16.11	17.66	5	2	3	4	1
FI	9.52	8.66	9.88	9.39	12.17	3	5	2	4	1
FR	15.13	12.45	13.90	8.03	17.82	2	4	3	5	1
DE	17.93	13.25	13.80	8.95	15.83	1	4	3	5	2
IE	16.07	13.03	10.36	6.47	19.00	2	3	4	5	1
IT	14.46	13.77	13.62	13.50	15.88	2	3	4	5	1
JP	8.99	8.33	7.86	8.15	9.97	2	3	5	4	1
NL	13.47	16.22	18.55	16.80	21.95	5	4	2	3	1
NZ	21.13	13.58	19.20	14.70	22.60	2	5	3	4	1
PT	14.01	11.93	14.25	10.09	14.89	3	4	2	5	1
ES	8.64	7.71	10.90	4.52	11.50	3	4	2	5	1
SE	6.12	6.61	8.97	8.26	10.67	5	4	2	3	1
CH	10.22	6.64	12.56	12.58	11.51	4	5	2	1	3
GB	4.96	4.61	5.44	5.33	6.69	4	5	2	3	1
Mean	12.87	11.28	12.65	10.10	15.41	3	3.7	2.9	4.2	1.2

Table 26: Variable importance, '80s

Country	m_diff	y_diff	p_diff	i_diff	e	m_diff	y_diff	p_diff	i_diff	e
AU	6.20	5.97	7.08	4.94	7.35	3	4	2	5	1
AT	30.16	23.14	24.22	23.81	30.77	2	5	3	4	1
BE	31.11	24.48	30.13	13.97	28.95	1	4	2	5	3
CA	12.32	9.13	14.88	8.80	15.89	3	4	2	5	1
FI	17.82	10.64	19.63	13.51	18.40	3	5	1	4	2
FR	16.31	19.31	17.72	10.39	19.91	4	2	3	5	1
DE	26.85	18.60	18.99	11.18	19.75	1	4	3	5	2
IE	25.55	20.24	20.32	10.79	26.86	2	4	3	5	1
IT	27.98	24.92	24.74	21.03	28.37	2	3	4	5	1
JP	19.81	19.86	18.71	14.95	19.13	2	1	4	5	3
NL	25.08	20.84	22.61	24.09	26.41	2	5	4	3	1
NZ	15.14	14.24	13.23	13.37	17.28	2	3	5	4	1
PT	26.92	23.30	29.18	18.60	27.82	3	4	1	5	2
ES	13.19	10.59	20.36	5.83	14.39	3	4	1	5	2
SE	16.94	11.69	15.69	10.82	16.05	1	4	3	5	2
GB	19.44	14.81	18.68	16.71	18.98	1	5	3	4	2
Mean	20.68	16.98	19.76	13.92	21.02	2.19	3.81	2.75	4.63	1.63

Table 27: Variable importance, '90s

Country	m_diff	y_diff	p_diff	i_diff	e	m_diff	y_diff	p_diff	i_diff	e
AU	19.63	18.79	18.00	16.25	18.16	1	2	4	5	3
AT	12.59	15.67	15.77	14.26	16.79	5	3	2	4	1
BE	11.34	11.11	10.60	10.62	11.74	2	3	5	4	1
CA	7.70	7.04	8.03	6.78	9.16	3	4	2	5	1
FI	11.51	8.25	8.42	11.65	11.83	3	5	4	2	1
FR	7.38	7.62	7.04	6.85	7.87	3	2	4	5	1
DE	13.61	15.90	16.44	14.10	15.74	5	2	1	4	3
IE	6.22	5.62	5.91	3.12	6.70	2	4	3	5	1
IT	6.08	8.85	8.44	8.71	9.20	5	2	4	3	1
JP	11.21	11.87	11.39	10.60	12.92	4	2	3	5	1
NL	13.73	14.72	12.74	15.53	14.92	4	3	5	1	2
NZ	33.32	21.11	22.90	20.10	24.56	1	4	3	5	2
PT	6.32	7.83	7.25	6.93	8.27	5	2	3	4	1
ES	12.80	12.18	14.35	13.38	15.21	4	5	2	3	1
SE	7.75	5.59	6.11	4.23	8.05	2	4	3	5	1
GB	6.35	6.64	7.74	8.52	10.37	5	4	3	2	1
Mean	11.72	11.17	11.32	10.73	12.59	3.38	3.19	3.19	3.88	1.38

Table 28: Variable importance: 2000s

Country	m_diff	y_diff	p_diff	i_diff	e	m_diff	y_diff	p_diff	i_diff	e
AU	15.78	14.17	14.99	13.19	18.46	2	4	3	5	1
CA	10.40	11.23	9.65	8.26	11.24	3	2	4	5	1
DK	15.96	16.68	16.31	16.11	17.66	5	2	3	4	1
JP	10.07	8.08	9.15	6.86	9.02	1	4	2	5	3
NZ	21.66	15.20	18.74	19.26	22.86	2	5	4	3	1
SE	13.87	14.54	15.31	18.23	18.79	5	4	3	2	1
CH	8.13	5.06	8.41	8.23	8.30	4	5	1	3	2
GB	5.36	4.76	5.99	4.59	5.73	3	4	1	5	2
Mean	12.65	11.21	12.32	11.84	14.01	3.13	3.75	2.63	4.00	1.50

Figure 22: Variable importance, out of sample 12 months ahead forecasts, SVM tool.

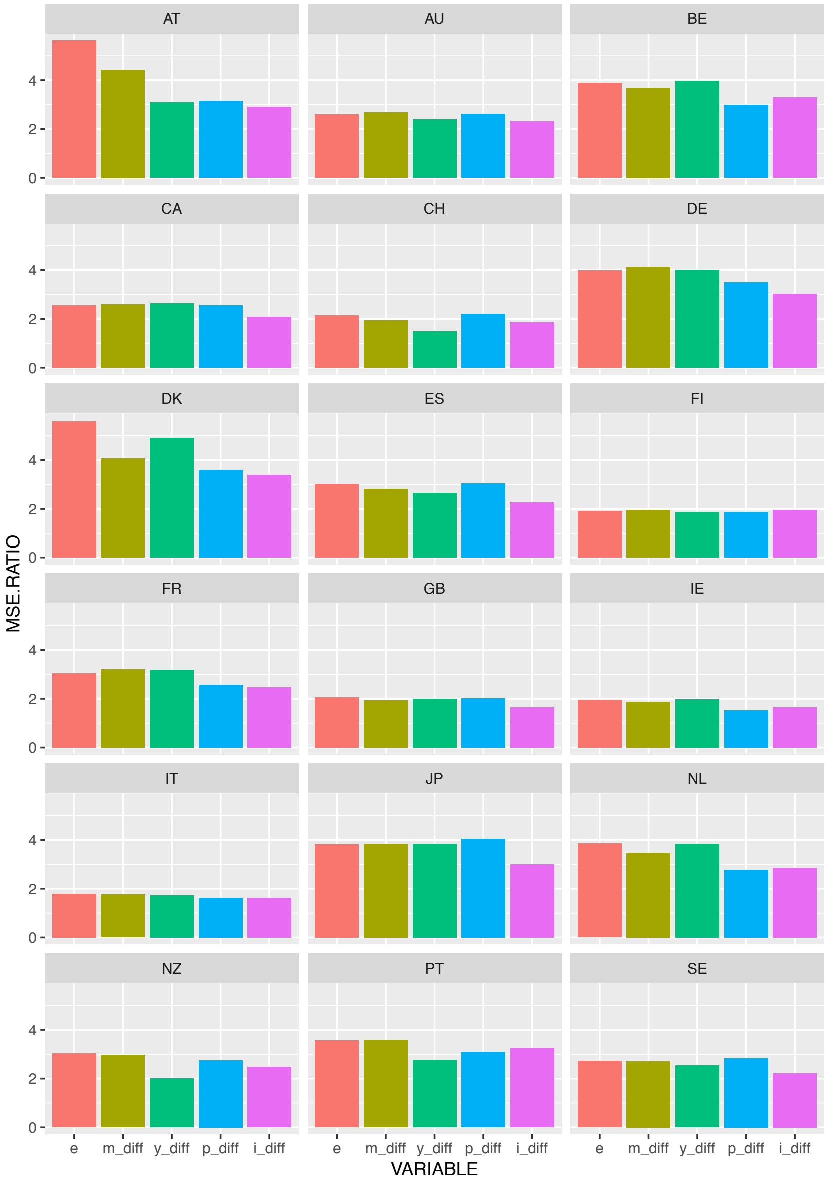

Figure 23: Partial dependence plots, 12 months ahead forecasts, SVM.

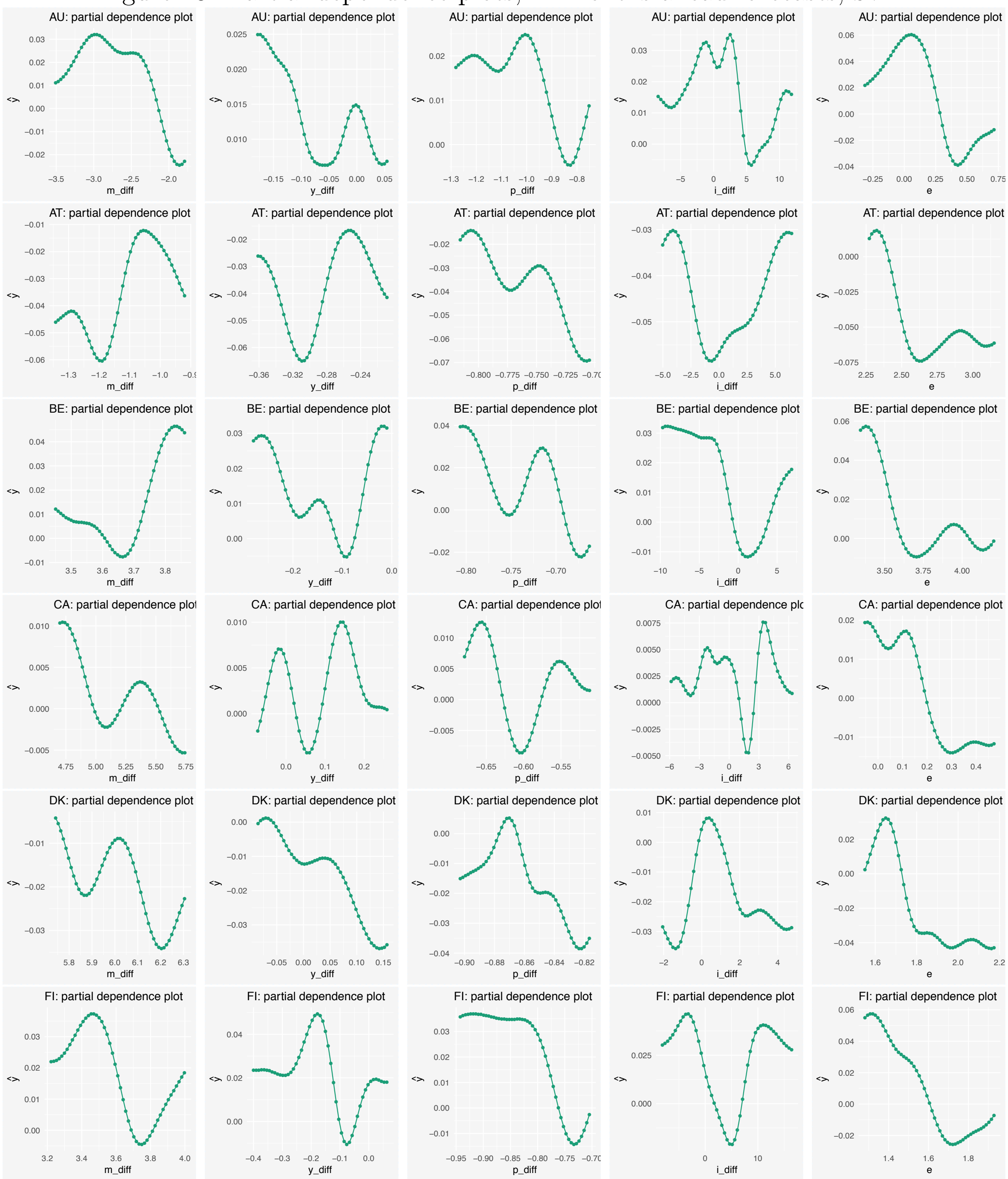

Figure 24: Partial dependence plots, 12 months ahead forecasts, SVM.

Figure 25: Partial dependence plots, 12 months ahead forecasts, SVM.