Factors influencing Foreign Exchange Rates: Exploring Relative Importance using Ensemble Methods

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Abstract

To analyze which factors influence changes in foreign exchange rates, most studies have focused extensively on linear models, assigning variable significance based on standard inferential statistics. However, implicit assumptions of these models impose structure on the relationship between exchange rates and macroeconomic forces, often restricting their out-of-sample predictive power. In this paper, I employ ensemble methods to predict out-of-sample exchange rates of nine different currencies against the U.S. dollar, using both a regression and classification approach. Input variables constitute monthly frequency macroeconomic data from different countries over varying periods of time between January 1975 and May 2018. After evaluating the predictive performance of the models, I compare the relative importance of different macroeconomic variables in estimating the values. I find that for different currencies, changes in relative consumer price indices have considerable predictive power, while the predictive power of other macroeconomic variables appear idiosyncratic to the currency pair.

1 Introduction

The movement of foreign exchange rates has long been, and continues to be, an elusive question among even the most accomplished economists, researchers and academics around the world. The studied persistence of their unpredictability at high frequencies has established wide held consensus that exchange rates follow a random walk. Though structural linear models have provided insight into various aspects of the relationship between exchange rates and other macroeconomic factors, they have generally performed poorly when relied upon to forecast them out-of-sample, often worse than a random walk model. Though this may not appear troubling at first, further inquiry and research over time has called their relevance into question, given that the true relationship is expected to predict exchange rates better than a random process.

Meese & Rogoff (1983) investigated out-of-sample forecasting accuracy of various structural and time-series exchange rate models in order to evaluate their predictive power over varying time periods. They applied candidate models such as flexible-price(Frenkel-Bilson) and sticky-price(Dornbusch-Frenkel) monetary models, including a sticky-price model incorporating current accounts(Hooper-Morton). From their study, Meese & Rogoff concluded that a random walk model predicts exchange rates as well as any of the structural models over one to twelve-month horizons for the dollar/yen, dollar/pound and trade-weighted dollar exchange rates. The criterion they used to compare model predictive power is RMSE. They attributed the poor performance of these models out-of-sample to a number of possible factors. They suspected simultaneous equation bias, sampling error, stochastic movements in the underlying parameters or even misspecification. They further anticipated that other singular events(two oil shocks) during the time periods evaluated could have contributed to parameter uncertainty, eventually affecting their predictive power. Their results, in contrast to previous studies that used in-sample fits, supported the view that out-of-sample fits constituted an important criterion for evaluating structural models. Structural models may have some explanatory power in determining exchange rates but their predictive performance out of sample is low because the parameters of the model itself need to be forecasted.

A number of studies followed after Meese & Rogoff (1983) that tried to reconcile the relevance of theoretical structural models. Woo (1984) re-estimated the monetary model of exchange rate determination after reformulating it to include money-demand functions that incorporated partial rather than instantaneous stock adjustment mechanisms. When used to make out-of-sample forecasts, he found that the model out-performed a random walk model, albeit over a very short time-horizon. Frenkel revisited the same question in 1984 building up on his earlier paper in 1979. Initially employing the sticky-price model, he found that variables such as relative money supplies, real-incomes and inflation expectations were insignificant. Only after making theoretical modifications to account for shifts in money-demand functions and long-term exchange rate changes were these variables found to be significant.

To follow up, Cheung et. al. (2002) rephrased and re-evaluated the same question twenty years later by including a wider set of models that had gained traction over the previous decade. These included the interest-rate parity, productivity-based and "behavioral equilibrium exchange rate" models. Their results yielded similar results as Meese & Rogoff (1983), with the random walk model outperforming the structural models regardless of the time horizon. In conclusion, Cheung et. al. discussed some limitations of their approach as well. They mention the imposed linearity of the models restrict possible functional non-linearities and regime switching. They also suggest that although systems-based predictions may perform better out-of-sample over short-horizons, doing so for cross-country frameworks was far too cumbersome for their analysis.

Mariano et. al. (2016) investigated factors effecting the real exchange rate in the Philippines between 1973 and 2014 using unrestricted vector autoregressive model to estimate the relationship between the response and macroeconomic variables such as GDP, volume of money flows, net foreign assets, budget deficits, import restrictions and oil prices. They found no evidence of long-run co-integration between the dependent and independent variables even though variance decomposition revealed that GDP and volume of money flow accounted for most of the real exchange rate movement.

It is clear from the results of these empirical studies that structural linear models, despite several efforts to refine them over time, have failed to outperform the predictive accuracy of random walk models in determining exchange rates out-of-sample. Moreover, the very nature of structural model estimation subjects it to many potential sources of vitiation. Due to these incumbent issues with estimating the true relationship between exchange rates and other macroeconomic variables, as is evident from the literature, this paper introduces a new perspective of evaluating the problem. The aim in this case is not to estimate any coefficients in possible but restrictive linear relationships, but to determine which macroeconomic variables are accurate predictors and therefore, significant determinants of the exchange rate. Although they lack an easy-to-interpret linear structure between the response and the predictors, ensemble methods which analyze the data by segmenting the predictor space can capture important interaction effects between different variables. This approach bypasses problems specific to linear models, including the presence of outlier events, as is common in time-series financial data, and estimates the unbiased *relative importance* of each explanatory variable in predicting the response. In assessing out-of-sample predictive accuracy, I use both a regression and a classification model to develop a more comprehensive view of possible relationships. I also test my models over larger samples than those in the previously mentioned studies to obtain more robust results.

2 Data

By definition, the exchange rate is the relative price of two national currencies, and should thus be determined by basic factors underlying the demands and supplies of those national money stocks. Aside from the money supplies, these factors would also include real income and interest rates - the latter reflecting expectations of future inflation paths. Though real incomes are not included in my model, it incorporates other important indicators relevant to the determination of exchange rates. Table 1(a) describes the various Macroeconomic indicators used as input variables. Table 1(b) displays sample sizes and time periods for which different exchange rates were studied. Exchange Rate data was obtained from the Federal Reserve Economic Database(FRED St. Louis) and data on monthly frequency macroeconomic variables were obtained from OECD statistics.

Table 1: Data Summary

(a) Explanatory Variables

Indicator	Description
Relative CPI*	Domestic Aggregate Price Level
Short-term IRs	Overnight - 90 day
Long-term IRs	10-year Bond Yields
Broad Money (M3)*	Supply of all Money
Narrow Money (M1)*	Supply of liquid Money
Share Prices*	Domestic Stock Market
Imports^{+}	Goods and Services Imports
Exports^{+}	Goods and Services Exports
Net Exports	Proxy for Monthly BOT

*Measured using 2010 as the base year, not s.a.

$^{+}$Measured in billions of U.S. dollars

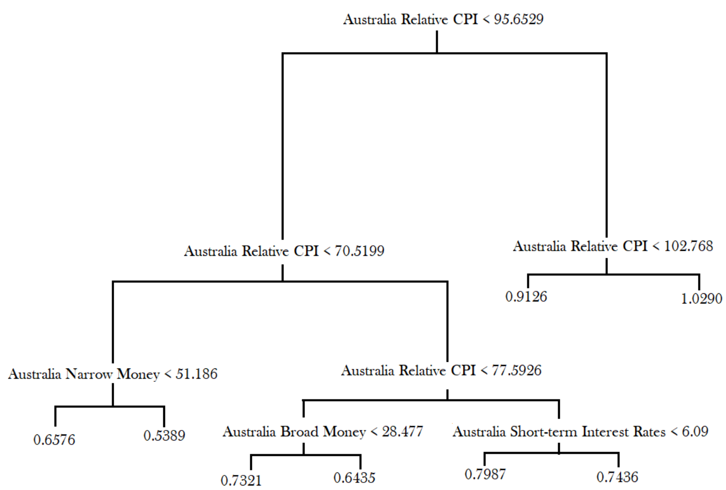
(b) Time Periods and Sample Sizes

Currency	Time Period	Sample Size
AUD/USD	August 1990 - May 2018	334
CAD/USD	January 1975 - May 2018	521
CHE/USD	January 1975 - May 2018	521
CNY/USD	January 1999 - April 2015	196
EUR/USD	January 1999 - May 2018	233
GBP/USD	January 1987 - May 2018	377
JPY/USD	April 2002 - May 2018	194
KRW/USD	October 2000 - April 2018	211
NZD/USD	January 1985 - May 2018	401

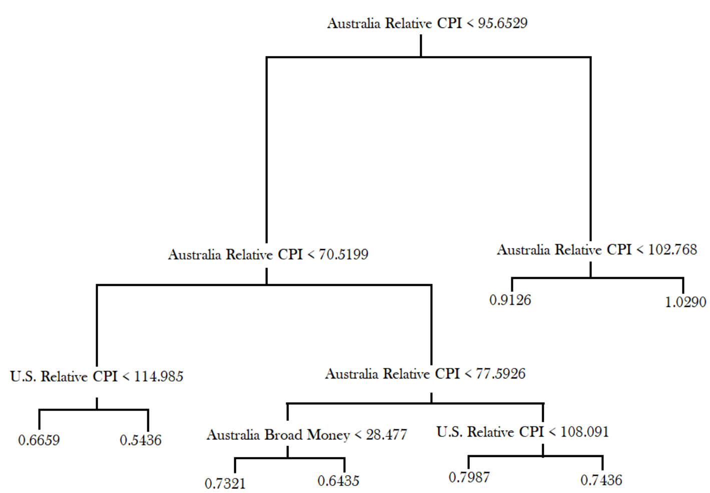
3 Methodology

3.1 Regression Tree

The first part of the analysis is to predict point estimates of the exchange rates for each currency using the input variables displayed in Table 1(a). Though 'Ensemble Methods' include any class of statistical models that create and combine several models, I examine the performance of three specific types of models - *bagging, boosting and random forests*[1] - all derived from Regression Tree models, but optimized for predictive accuracy. To put it simply, a regression tree divides the predictor space (in this case, the macroeconomic variables used) into a number of distinct and non-overlapping regions. For any observation that falls into a particular region, the tree predicts the mean of the response values for training observations that belong to the same region. Trees use *recursive binary splitting*[1] to obtain optimal tree structure by iteratively updating the tree to minimize the *root-mean squared error* (RMSE).



(a) Australian Macroeconomic Variables



(b) Australian and U.S. Macroeconomic Variables

Figure 1: Pruned Classification Trees for AUD/USD

[1] James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013) An Introduction to Statistical Learning with Applications in R. Tree-Based Methods (Chap. 8 pp. 303-331)

Figure 1 shows two pruned regression trees for predicting monthly averages in the AUD/USD exchange rate using a combination of different macroeconomic variables as inputs. Both trees were pruned after cross-validating to determine how many terminal nodes reduce the mean-squared error the most. Figure 1(a) shows an eight terminal node tree constructed by using only domestic (Australian) macroeconomic variables in the model. Figure 1(b) shows a tree with eight terminal nodes and was constructed by using both domestic as well as foreign (U.S.) macroeconomic input variables.

The length of the branches represent the relative importance of those macroeconomic variables in determining the response values (in this case, monthly averages of exchange rates). The relative importance of variable is determined by the mean increase in the MSE by dropping it out of the model. Notice that Relative CPI appears to be the most important variable in predicting the exchange rate. This applies for both graphs above, with domestic relative CPI having a stronger influence on predicting the monthly averages of the AUD/USD, than foreign relative CPI. In Figure 1(b), the inclusion of other macroeconomic variables such as domestic broad money supply marginally improves the predictive performance of the regression tree.

For better predictive performance, we use three methods - bagging, boosting and random forests. In bagging, we randomly draw observations with replacement from the training set to produce bootstrapped samples. We then fit deep regression trees to each of these bootstrapped samples, obtaining a new tree for each sample. Aggregating over all the trees, a prediction is made as the mean of the response values of all training observations belonging to the same region as that of the input observation. Although this approach leads to considerable improvement in prediction accuracy over a single regression tree, the presence of relatively few important predictors imply higher variance in the (averaged) predictions. This is because many of the bootstrapped trees are correlated due to the presence of the same strong predictors in all of them. To reduce this variance and get more stable predictions, random forests are used. By using only a random sample of the predictors to fit each bootstrapped sample, the fitted trees in a random forest are less correlated with one another. Boosting is the third and final method used to fit our models. In boosting, shallow trees are sequentially fitted to the residuals of each previously fitted tree and then added together to obtain the final predictive model. For each evaluation, the model is first trained on 70% of the observations i.e. the training set; predictions are then made on the remaining 30% of observations i.e. the test set.

3.2 Classification Tree

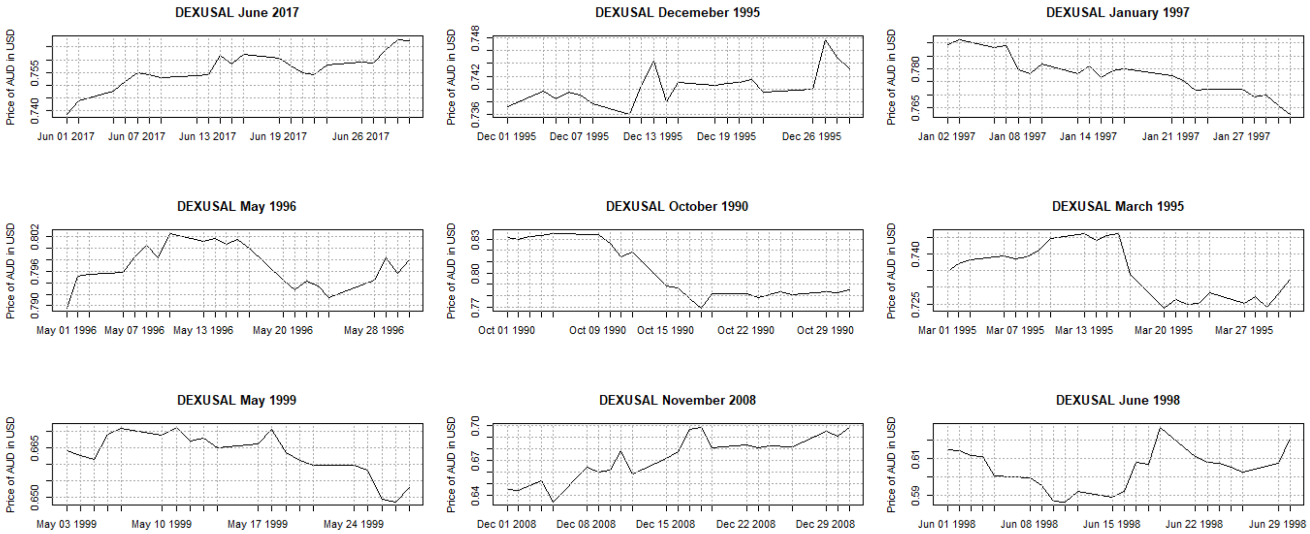
In the second part of the analysis, we first classify each month as either having experienced an overall upward or downward trend in the exchange rate throughout the month. We then use the same models discussed in Section 3.1 to accurately classify monthly trends as either being Up, Down or Ranging (i.e. having no clear direction). The Aroon Indicator[2] is used to meaningfully design response values. In essence, the indicator measures the time it takes for the price to reach the highest and lowest points over a given timeframe as a percentage of total time (N). In practice, most traders and experts use N = 25, but since the average number of days per month in our dataset is 21, the indicator may identify monthly changes in trends more precisely using this value. The formulas are given as:

$$\textbf{AroonUp} = \frac{\text{21 - Days since 21-day High}}{21} \times 100 \qquad \textbf{AroonDown} = \frac{\text{21 - Days since 21-day Low}}{21} \times 100$$

To construct our response vector, we first calculate daily AroonUp and AroonDown values of the exchange rates for each currency pair using N = 21. Each month is then assigned the average of both these values over all days in that month. If the AroonUp average is measured at above 70, while the AroonDown average is measured at below 30 for a particular month, the market is considered to be predominantly facing an upward pressure in that month, and its indicator response is assigned to be 1. When the AroonUp is below 30 and AroonDown is above 70 i.e. a reversal of the previous condition, the market predominantly faces downward pressures throughout the month and is assigned an indicator response equal to -1. For all Aroon values between these ranges, the indicator response is assigned as 0, indicating absence of any clear directional pressure on the exchange rate for that month. This may be considered a crude measure of classifying monthly trends for different currency pairs, but can still be argued to provide some information on directional movements in exchange rates from month to month.

Figure 2 displays visual plots of the daily movements in the AUD/USD exchange rate for different month-year periods, which were assigned different trends responses. The trends displayed on the top panels for all three indicator responses represent the ideal visual plots of exchange rate trends for their respective indicators. However, from the graphs displayed, it is evident that such is not always the case. In Figure 2(a), the middle and lower plots show some downward movements in the AUD/USD exchange rate for May 1996 and 1999 despite being classified as upward trending. Similarly, for Figure 2(b) where Indicator = 0, the middle and lower graphs appear to show downward and upward trends for October 1990 and November 2008 respectively. In Figure 2(c), two graphs reflect fluctuating exchange rates for the months of March 1995 and June 1998 despite being classified as strictly downward trending.

[2]The Aroon indicator is a technical indicator used to identify when trends are likely to change direction. Source: Investopedia



(a) Indicator = 1 (b) Indicator = 0 (c) Indicator = -1

Figure 2: Monthly Trends for AUD/USD Exchange Rate

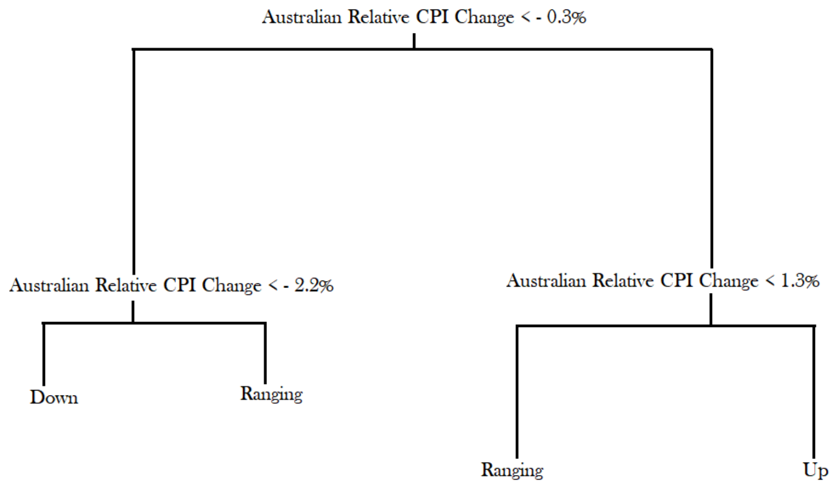
Despite these discrepancies, it is important to remember that the indicator responses are assigned based on the average of the realizations of the AroonUp and AroonDown values for all the days in these months. Thus, they may not appear to follow a uniform and gradual upward or downward trend through the entire month, but the exchange rate faces an upward or downward pressure for most part of the period. If it experiences upward and downward pressures equally, or such that the threshold values of above 70 and below 30 are not jointly exceeded, the monthly trend is assigned an indicator response = 0, which classifies the trend as 'ranging'.

Assuming that changes in macroeconomic variables in the economy stimulate corresponding changes in the foreign exchange market through different linkages, I use percent changes of those displayed in Table 1(a) for all currency pairs as my explanatory variables in the classification problem. The percent changes are calculated month to month and convey information about the marginal changes in macroeconomic variables from one period to the next. They represent both the direction and magnitude of changes in these variables. In addition, they allow cross-country variables to be used in the same model without accounting for differences in units or scales.

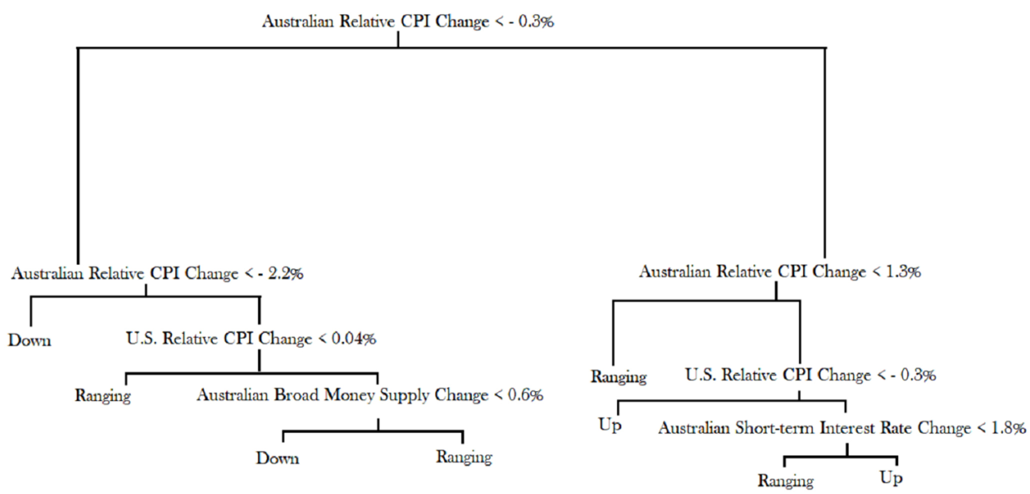
3.3 The Classification Tree Model

A classification tree works the same way a regression tree does, except now, for any observation that falls into a particular region, the tree classifies(predicts) the response as the most commonly occurring class among the training observations that belong to the same region. Similar to regression trees, they also use recursive binary splitting to obtain optimal tree structure by iteratively updating the tree to minimize the *classification error rate*.

Figure 3 shows two pruned classification trees for predicting monthly trends in the AUD/USD exchange rate using a combination of different macroeconomic variables as inputs. Both trees were pruned after cross-validating to determine how many terminal nodes reduce the classification error rate the most. Figure 3(a) shows a four terminal node tree constructed by using only domestic (Australian) macroeconomic variables in the model. Figure 3(b) shows a tree with 8 terminal nodes and was constructed by using both domestic as well as foreign (U.S.) macroeconomic input variables. Once again, changes in domestic and foreign relative CPI appear as the most important variables in predicting the monthly trend values. In Figure 3(b), aside from changes in domestic money supply, changes in domestic short-term interest rates are also included to improve the classification accuracy of the model.



(a) Australian Macroeconomic Variables



(b) Australian and U.S. Macroeconomic Variables

Figure 3: Pruned Classification Trees for AUD/USD

4 Results

4.1 Prediction of Monthly Averages

Table 2 displays the R.M.S.E. estimates of out-of-sample predictions of all three models for the AUD/USD using only domestic (Australian) macroeconomic variable data. The bagging and random forest models show the best results for most of the currencies; the boosted model outperforms both the bagged and random forest models only for the EUR/USD. In Table 3, the R.M.S.E. estimates are from the same models, but using both domestic (Australian) and foreign (U.S.) macroeconomic variables as inputs. The estimates in bold signify the lowest R.M.S.E. estimate for that exchange rate after comparing all the models over both sets of input variables. Using both domestic and foreign macroeconomic data unambiguously improves the predictive performance of the models, with the bagged and random forest models performing relatively well. The boosted model outperforms both for the EUR/USD and the KRW/USD.

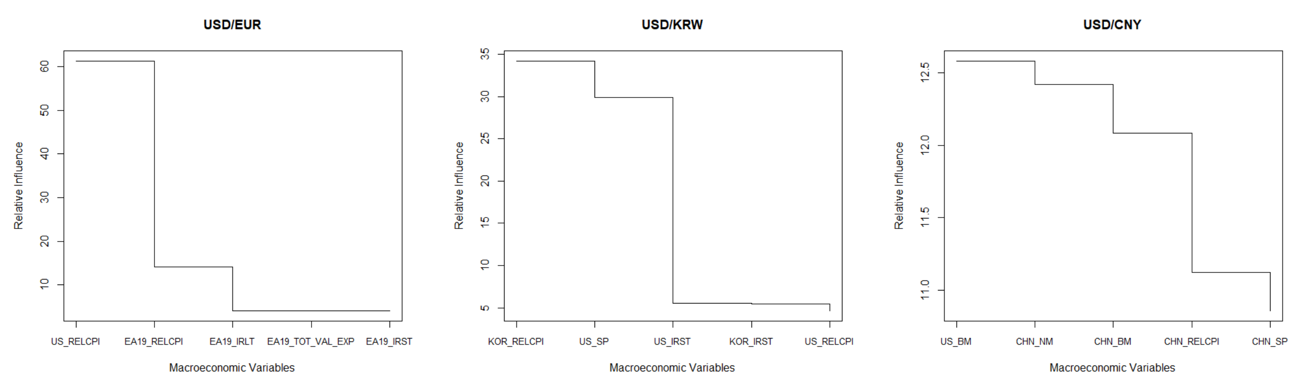
Table 2: R.M.S.E. estimates using only Domestic Macroeconomic Variables

Model	Bagging	Random Forest	Boosting
AUD/USD	0.0152	0.0162	0.0190
CAD/USD	0.0167	0.0137	0.0220
USD/CHF	0.0505	0.0492	0.0645
CNY/USD	0.0391	0.0373	0.0427
EUR/USD	0.0352	0.0355	0.0300
GBP/USD	0.0460	0.0473	0.0602
JPY/USD	2.0568	1.9786	2.5529
KRW/USD	27.9164	33.3275	29.0778
NZD/USD	0.0156	0.0150	0.0163

Table 3: R.M.S.E. estimates using both Domestic and Foreign (U.S.) Macroeconomic Variables

Model	Bagging	Random Forest	Boosting
AUD/USD	**0.0136**	0.0159	0.0153
CAD/USD	**0.0132**	**0.0132**	0.0187
USD/CHF	0.0448	**0.0439**	0.0559
CNY/USD	0.0330	**0.0325**	0.0375
EUR/USD	0.0291	0.0288	**0.0215**
GBP/USD	**0.0417**	0.0440	0.0482
JPY/USD	**1.7708**	1.8425	2.2034
KRW/USD	27.9271	30.6090	**25.7394**
NZD/USD	**0.0125**	0.0148	0.0133

We should note that all of these estimates were derived from predictions on out-of-sample monthly exchange rate data. The models were fitted specifically on 70% of the data in each sample and then used to predict exchange rates for the remaining 30% of the sample. These out-of-sample observations are randomly chosen and are not chronological, though efforts could've been made to make them such. Taking a random sample of observations to test our model predictions out-of-sample is a more robust method of estimating the true relationship between exchange rates and macroeconomic variables, as these observations can be regarded as independent of one another. Depending on the sample sizes for each of the currencies, these test sets contain between 58 observations (JPY/USD) to 156 observations (CAD/USD).

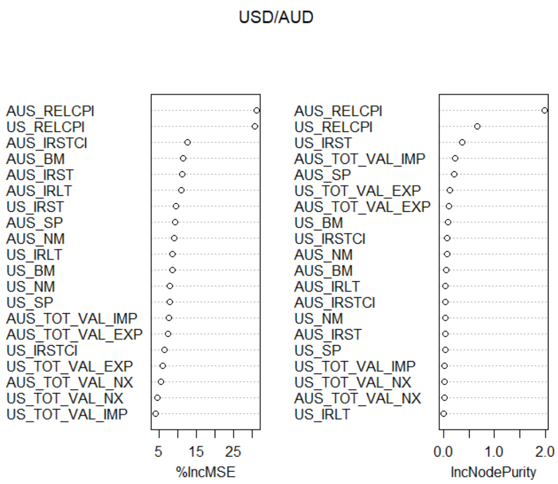


(a) Boosted Model (b) Boosted Model (c) Random Forest Model

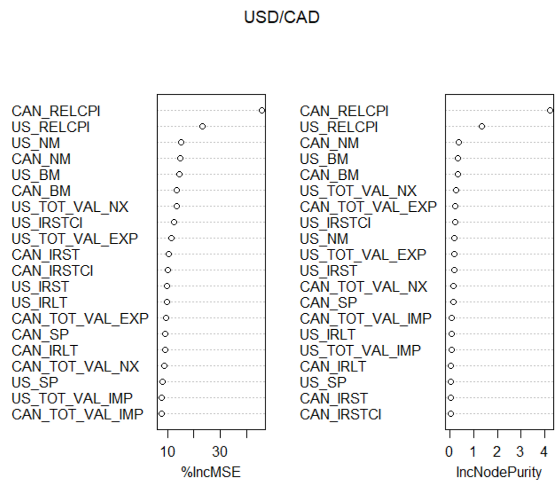
Figure 4: Variable Importance plots for optimal models

Choosing only the models with the lowest RMSE estimates for each currency pair, we examine the *Relative Influence*[3] plots for each model to determine which macroeconomic variables contributed the most in predicting the exchange rate. The rankings are determined by relevant measures such as the percentage increase in the

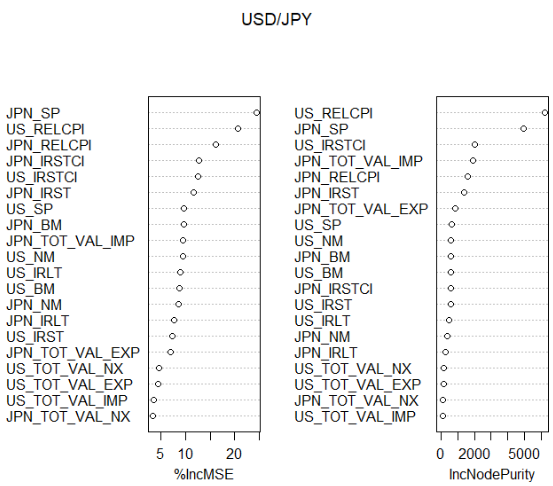
[3]Relative Influence measures the importance of each variable in prediction by calculating RSS (for regression) and Gini Index (for classification) decreases resulting from their addition to the models.



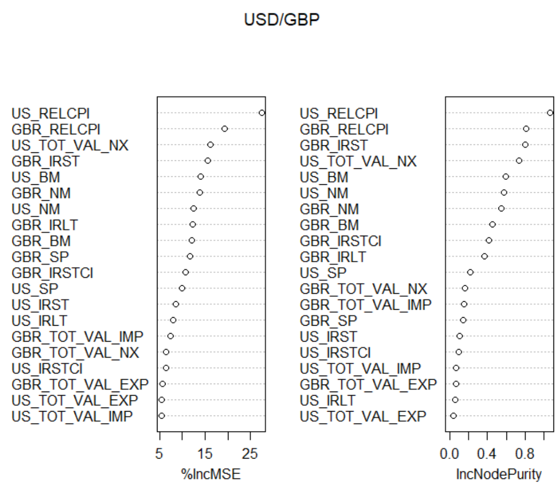
(a) Bagged Model



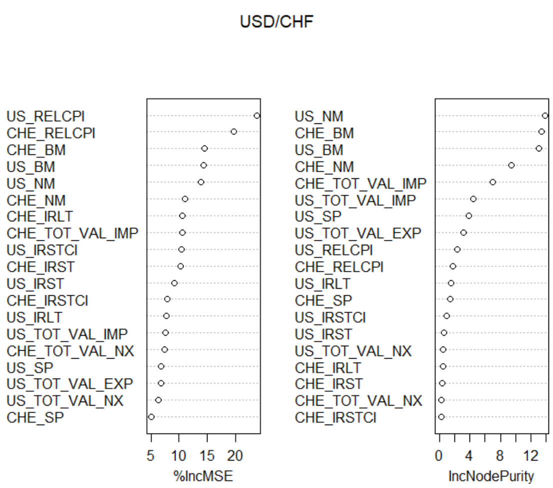
(b) Bagged Model



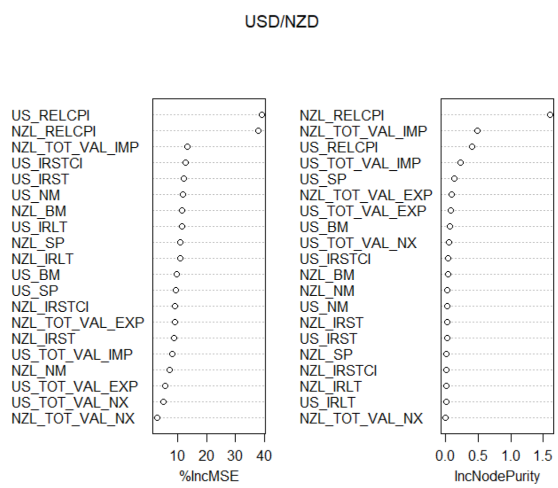
(c) Bagged Model



(d) Bagged Model



(e) Random Forest Model



(f) Bagged Model

Figure 5: Relative Influence plots for all optimal models

mean-squared error (MSE) or total decrease in *node impurity*[4]. For our purposes, we use the former (i.e. reduction in MSE) to ascertain which macroeconomic variables have the highest predictive power.

Figures 4 and 5 show relative importance plots for all the variables used in the models with the lowest RMSEs for different currency exchange rates. For most currencies, the top two variables with the highest predictive power are domestic and foreign relative CPIs. For the CAD/USD, AUD/USD, EUR/USD, KRW/USD and the NZD/USD, the difference in predictive power between these variables and any other macroeconomic variables is significant, implying that the latter might provide little to no information in predicting the response. In Figures 4(c), 5(c) and 5(d), this is not the case. For the CNY/USD, JPY/USD and GBP/USD, other macroeconomic forces also appear to be relatively important in determining the exchange rate. These variables include monetary aggregate variables like broad and narrow money supplies, short-term interest rates and share prices.

4.2 Classification of Monthly Trends

Table 4 displays the results of applying all three models to predict out-of-sample trend values given using month-to-month percent changes in domestic macroeconomic variables as inputs. Table 5 displays the same results but uses both domestic and foreign (U.S.) macroeconomic variables as inputs. For both the analyses, the boosted models were cross-validated to obtain the optimal number of trees that resulted in the lowest classification error rate. Though for most models, this led to an improvement in the classification rate, some models such as AUD/USD, CNY/USD, NZD/USD, JPY/USD and EUR/USD experienced deteriorations in their predictive performance. They are marked with an '*'.

Table 4: Classification Rates using only Domestic Macroeconomic Variables

Exchange Rate	Bagging	Random Forest	Boosting
AUD/USD	0.73	0.68	**0.75**
CAD/USD	0.65	0.62	0.67
CHE/USD	0.60	0.63	0.63
CNY/USD	0.64	0.64	0.61
EUR/USD	0.66	0.66	**0.66***
GBP/USD	0.55	0.60	0.65
JPY/USD	**0.72**	0.67	0.67*
KRW/USD	0.54	0.54	**0.62**
NZD/USD	0.68	0.68	0.65

Similar to the regression tree analysis, different model specifications result in different classification rates, even within the same sample. What is interesting is that the predictive power of the models using both foreign and domestic macroeconomic variables is not always superior to those using only domestic variables. Table 6 summarizes the results from Table 4 & Table 5. We see that a boosted model performs consistently well across six of the chosen nine exchange rates. The bagging and random forest models outperform the boosted models for only the JPY/USD, CHE/USD and CNY/USD. For four exchange rates, namely the AUD/USD , EUR/USD, JPY/USD and KRW/USD, using only changes in domestic macroeconomic indicators as the inputs in the models yield better predictive performance than incorporating additional information on changes in U.S. macroeconomic variables. For the other currencies, including information on both domestic and foreign macroeconomic variables in the sample improve the predictive performance of the models.

In Figure 6, we investigate the relative importance for six of the currencies that had the highest out-of-sample classification rates in a boosted model. For five of them, namely the AUD/USD, CAD/USD, NZD/USD, EUR/USD, and KRW/USD, the most important variable for determining monthly trends in the exchange rate is changes in domestic Relative CPI. For the GBP/USD, changes in Foreign (U.S.) Consumer Price Index has higher predictive power. For Figure 3(b), 3(d) and 3(f), notice that the optimal models for monthly trend prediction incorporate both domestic and foreign macroeconomic changes. For the CAD/USD and NZD/USD, the second most important variable is changes in U.S. Consumer Price Index; for the GBP/USD, it is changes in its domestic (U.K.) Relative CPI.

Aside from the large influence of changes in Relative CPIs as is evident in all the plots, notice that for specific currencies, changes in other macroeconomic variables also have some predictive power, albeit very small compared to Relative CPIs. For the AUD/USD, changes in monetary aggregates (broad and narrow money supplies), long-term interest rates and imports convey some information about the directional movement of the AUD/USD exchange rate. Similarly, changes in monetary aggregates and short-term interest rates also

[4]Node Purity is measured by the *Gini Index* or *Cross-Entropy* i.e. total variance across K classes of the response.

Table 5: Classification Rates using both Domestic and Foreign (U.S.) Macroeconomics Variables

Exchange Rate	Bagging	Random Forest	Boosting
AUD/USD	**0.75**	0.73	0.73*
CAD/USD	0.70	0.67	**0.71**
CHE/USD	0.70	**0.72**	0.71
CNY/USD	**0.69**	**0.69**	0.63*
EUR/USD	0.60	0.57	0.57
GBP/USD	0.67	0.69	**0.71**
JPY/USD	0.69	0.69	0.67
KRW/USD	0.52	0.54	0.56
NZD/USD	0.72	0.73	**0.73***

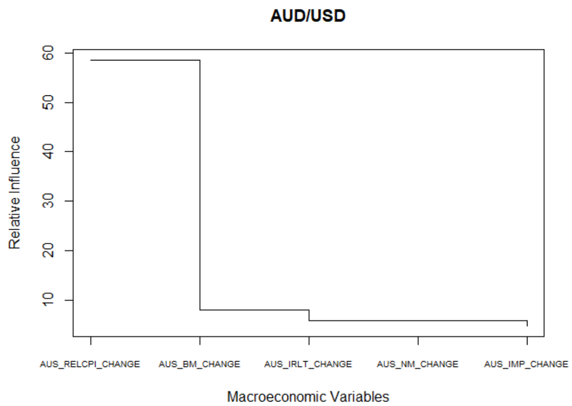
Table 6: Best Models for Predicting Monthly Trends

Exchange Rate	Input Variables	Model	Classification Rate
AUD/USD	D	Boosting	0.75
CAD/USD	D + F	Boosting	0.71
CHE/USD	D + F	Random Forest	0.72
CNY/USD	D + F	Bagging, Random Forest	0.69
EUR/USD	D	Boosting	0.66
GBP/USD	D + F	Boosting	0.71
JPY/USD	D	Bagging	0.72
KRW/USD	D	Boosting	0.62
NZD/USD	D + F	Boosting	0.73

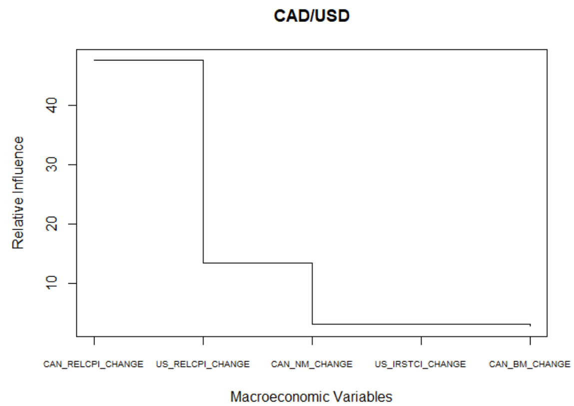
provide some, though little information in determining the CAD/USD exchange rate trend. In figure 3(c), we see that monthly trends in the Euro are determined using additional information on imports, changes in share prices, monetary aggregates (broad money) and short-term interest rates. For the GBP/USD, changes in domestic monetary aggregate variables and short-term interest rates add useful, though relatively little information. For the South Korean Won, changes in domestic share prices, broad money supply, imports and short-term interest rates marginally improve the models predictive accuracy. In figure 3(f), trends in the NZD/USD is predicted using information from changes in the domestic and foreign relative CPIs. However, changes foreign (U.S.) net exports, broad money supply and domestic long-term interest rates also appear to convey some useful information in their prediction.

Figure 7 gives us variable importance plots for all the models that out-performed boosted models for three specific currencies - USD/CHF, CNY/USD and JPY/USD. In the cases of the Swiss Franc and the Japanese Yen, we arrive at similar conclusions as before i.e. changes in domestic and foreign relative CPIs have the highest predictive power in determining their respective monthly trends against the U.S. dollar. Other macroeconomic variables that convey useful information in their prediction, though relatively little, are changes in short-term interest rates, broad money supplies and the level of imports and exports.

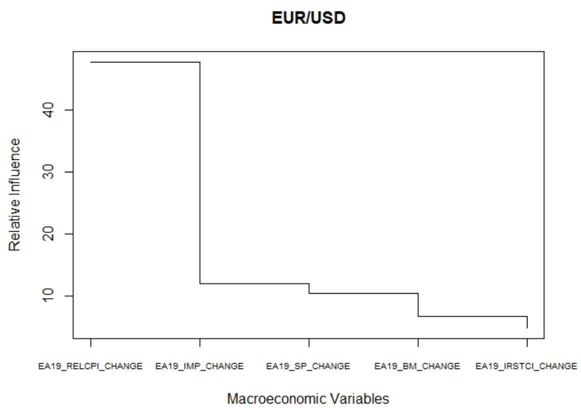
Finally, figure 7(c) and 7(d) give us variable importance plots for bagging and random forest models used to predict monthly trends in the CNY/USD exchange rate. These are different from all of the previously examined plots in that relative CPIs do not occupy the top position in the ranking of important variables. In fact, domestic and foreign relative CPIs contain lesser information than other macroeconomic variables which, in the previous cases contained little to no predictive power in determining exchange rate trends of the other currencies. From examining the plots, we see that both the bagging and random forest models list out changes in U.S. share prices, money supplies (both broad and narrow money) and imports as the variables with the highest Relative Influence. While the bagging model favors information conveyed by changes in U.S. relative CPI over changes in U.S. short-term interest rates, the random forest model favors the opposite. In both cases, note that changes in domestic (China) macroeconomic variables contain relatively less information in predicting the CNY/USD exchange rate than changes in U.S. macroeconomic variables. This result is discussed in further detail in the final section of the paper.



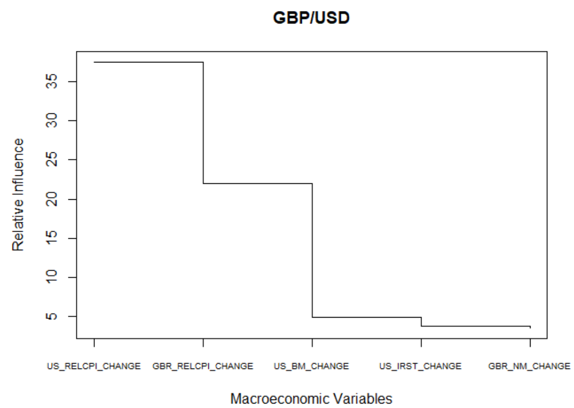
(a) Boosted Model (D)



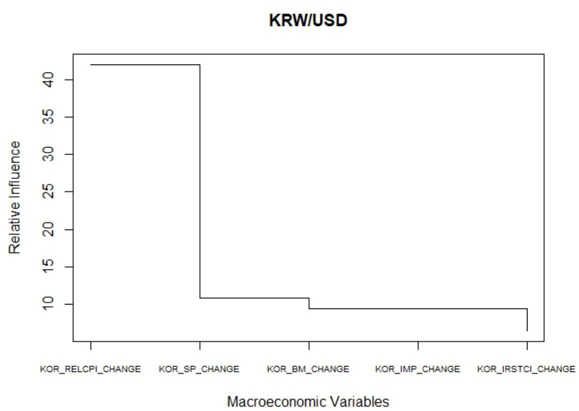
(b) Boosted Model (D+F)



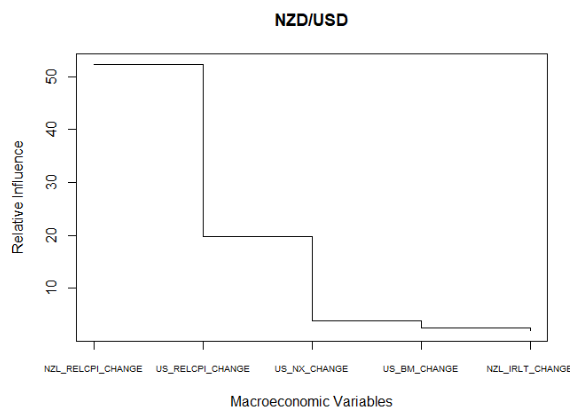
(c) Boosted Model (D)



(d) Boosted Model (D+F)

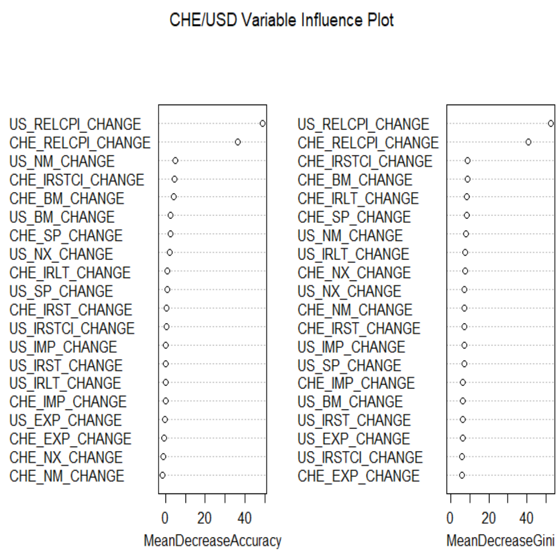


(e) Boosted Model (D)

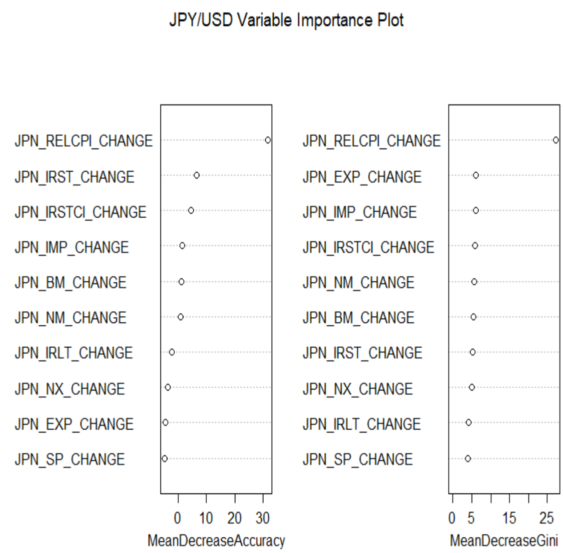


(f) Boosted Model (D+F)

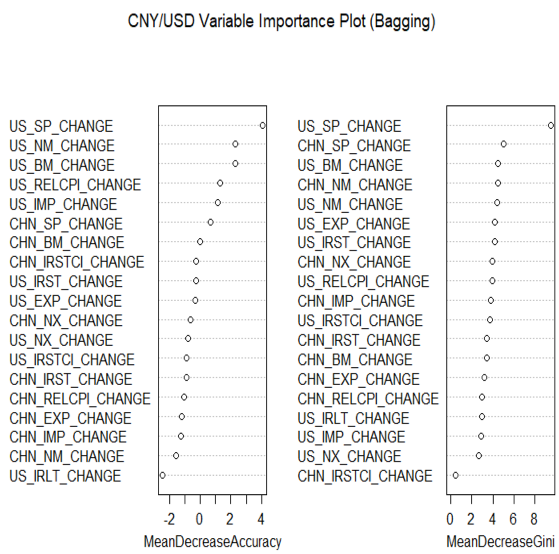
Figure 6: Variable Importance plots for all optimal Boosted models



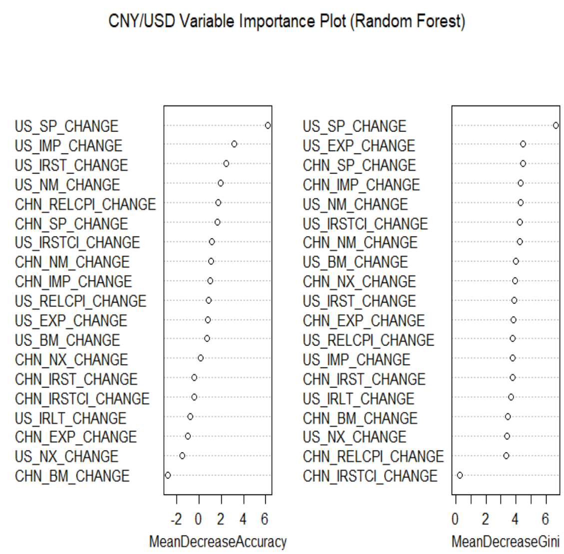
(a) Random Forest Model (D+F)



(b) Bagging Model (D)



(c) Bagging Model (D+F)



(d) Random Forest Model (D+F)

Figure 7: Variable Importance plots for all other optimal models

5 Conclusion

Exchange rate models have traditionally been modeled with the application of structural linear models since the time of their inception. Wherever required, researchers have made various adjustments, modifications and reformulations of the existing models to better understand the true relationship between exchange rates and other macroeconomic variables. As previously discussed, though individual studies have found structural models to provide some explanatory power in determining exchange rates, they have failed to explain their poor out-of-sample forecast accuracy. When a random walk model is able to predict exchange rates better than a structural model, the relevance of the estimated structural model is called into question, given that a true relationship is expected to predict exchange rates better than a random process. Perhaps, the true relationship is far more complicated than a linear model could accurately capture.

Meese & Rogoff (1983) emphasize out-of-sample forecast accuracy as an important criterion for evaluating the relevance of such models. This is precisely why we explore the performance of ensemble models in making out-of-sample predictions on the exchange rates of different currencies. The approach is different from traditional studies where linear models are pre-dominant for their convenience of construction and interpretation. By applying ensemble methods, out-of-sample prediction accuracy is the foremost criterion used to evaluate the merit of the fitted models. Although they may not be linear, they can capture important interaction effects between different variables in estimating the response. Moreover, they provide information on the *relative influence* of each variable in making those estimates, as represented in Figures 1 and 3. Table 7 & 8 show the top five variables with highest predictive powers in both the regression and classification ensembles used in our analysis.

Table 7: Variable Importance Plots Summary for Regression Tree

Exchange Rate	**Variables in order of Relative Influence**
AUD/USD	Australia relative CPI, short-term interest rates and broad money supply, U.S. relative CPI,
CAD/USD	Canada relative CPI and narrow money supply, U.S. relative CPI, narrow and broad money supply
USD/CHF	U.S. relative CPI, broad and narrow money supply, Switzerland relative CPI and narrow money supply,
CNY/USD	U.S. broad money supply, China narrow money supply, broad money supply, relative CPI and share prices
EUR/USD	U.S. relative CPI, European Union relative CPI, long-term interest rates, total value of exports and short-term interest rates
GBP/USD	U.S. relative CPI, total value of net exports and broad money supply, U.K. relative CPI and short-term interest rates
JPY/USD	Japan share prices, relative CPI and short-term interest rates, U.S. relative CPI and short-term interest rates
KRW/USD	Korea relative CPI and short-term interest rates, U.S. share prices, short-term interest rates and relative CPI
NZD/USD	U.S. relative CPI and short-term interest rates, New Zealand relative CPI and total value of imports,

Table 8: Variable Importance Plots Summary for Classification Tree

Exchange Rate	**Variables in order of Relative Influence**
AUD/USD	Australia relative CPI, broad money supply, long-term interest rates, narrow money supply and total value of imports
CAD/USD	Canada relative CPI, broad and narrow money supply, U.S. relative CPI and short-term interest rates
CHE/USD	U.S. relative CPI and narrow money supply, Switzerland relative CPI, short-term interest rates and broad money supply
CNY/USD	U.S. share prices, broad and narrow money supplies, total value of imports and short-term interest rates, China relative CPI
EUR/USD	European Union relative CPI, total value of imports, share prices, broad money supply and short-term interest rates
GBP/USD	U.S. relative CPI, U.K. relative CPI, broad and narrow money supply and short-term interest rates
JPY/USD	Japan relative CPI, short-term interest rates, total value of imports and money supplies (broad and narrow)
KRW/USD	Korea relative CPI, share prices, broad money supply, total value of imports and short-term interest rates
NZD/USD	New Zealand relative CPI and long-term interest rates, U.S. relative CPI, total value of net exports and broad money supply

Though some macroeconomic variables show high predictive power in determining exchange rates, this tells us nothing about the direction of cause and effect in their relationship. However, our results suggest that the models have substantially higher predictive power than making random guesses about both the monthly averages, as well as the monthly trend values. Using log-transformed values of exchange rates for the JPY/USD and the GBP/USD like in Meese & Rogoff (1983), we found the RMSE estimates for out-of-sample 1 month predictions to be significantly lower than that of the random walk model they used, albeit the datasets and time periods studied are different; the classification trees also consistently predict out-of-sample responses at higher than 50% accuracy. There is no single metric on which the performance of our models can be compared with those in Meese & Rogoff (1983). However, given the performance of the models using much larger test samples, it can be argued that the information conveyed by the input variables must be significant to accurately predict the exchange rate - both in point estimation and trend classification.

In both tables, we see that relative consumer price indexes, whether domestic or foreign, show consistently high predictive power in determining both the direction and magnitude of changes in different currency exchange rates. The large difference in predictive power of CPI and that of other macroeconomic variables suggest that either, (1) they have significant influence over exchange rate movements, or (2) they are significantly influenced themselves by exchange rate movements, or (3) both are influenced by some external factor in some defined way.

From an economic standpoint, one would expect rising inflation in one country to depreciate the value of domestic currency relative to foreign currencies, as exports become more competitive and imports reduce. By examining simple pruned classification trees, this theory could explain the decision rule for classifying monthly trends for most of the currencies. However for some currencies such as the AUD/USD, GBP/USD and NZD/USD, the decision rule implied an opposite relationship. For the case of the AUD/USD, splitting rules of the classification tree in Figure 3 appear counterintuitive. For a less than -2.2% change in the domestic relative CPI (deflation) in a month, the trend for the AUD/USD is 'Down', while that of a month experiencing above 1.3% inflation is 'Up'. These results are inconsistent with what the theory suggests, but it could be that the exchange rate trend itself leads to deflating domestic price levels. For example, if a depreciating AUD/USD increases exports and reduces domestic import demand, large increases in domestic supply to meet these demands might consistently deflate domestic price levels over the course of a month. Alternatively, it could be that some other external force influences both variables to change simultaneously or acts as an indirect link between the two, making it appear as if they are directly related to one another; future expectations of lower interest rates during the months of deflation lead to capital flight from the domestic economy over an extended period of time, causing the exchange rate to depreciate during those months.

The above analysis is not a definitive argument to establish any causal relationship between changes in the relative CPI and exchange rate movements. In fact, the independent effect of each variable on the exchange rate is difficult to ascertain. However, interactions between different macroeconomic variables are well captured. Though money supply is a common factor, note that for different currencies, the other macroeconomic variables with high predictive power are not necessarily the same. This can be attributed to idiosyncratic characteristics of different economies resulting in dissimilar linkages between macroeconomic forces and movements in their respective foreign exchange markets with respect to the U.S. dollar. For example, China's exchange rate seems to be solely determined by changes in U.S. macroeconomic variables - very different from the general pattern of all other currencies. However, this makes sense when we account for China's strict capital controls, tightly held exchange rate by means of central bank interventions and stable interest rates over long periods of time. As a result, changes in the monthly trend of the CNY/USD is solely determined by factors outside of China's controlled macroeconomic environment, where change is slow and their effects limited.

In conclusion, my analysis does not prove the irrelevance of structural models and their ability to accurately approximate the true relationship between macroeconomic forces and exchange rate movements; indeed they provide information on important aspects of this relationship. Instead, it discusses the merits of using other statistical techniques like ensemble methods which, through their higher predictive performance out-of-sample, may provide deeper insight into the form and nature of these relationships. The methodology used to classify each month into trend categories may have resulted in the loss of information useful to the analysis and therefore, warrants further research to draw better parallels between the performance of these models and those discussed in Section 1. Further research should also be directed at understanding the true relationship between changes in relative CPI of different economies and their currency exchanges rates taking idiosyncratic features into consideration. Based on the results of this paper, it appears possible to accurately estimate the trend and value of monthly exchange rates using forecasted estimates of the domestic and foreign relative CPIs. Research into methods of doing this may further the scope and prospects of this analysis in the future.

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Supplementary Material

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