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Abstract

The USD/CNY exchange rate exhibits very different pattern in different periods as it changes wildly from one period to another according to the economic reforms and policies. This paper compares the performance of six different forecasting models of USD/CNY exchange rate under three different forecast scenarios from 2005-2015. In particular, the paper focuses in answering the following questions. (i) Do models' forecast performance change when the marketization level changes? (ii) Which model has the best forecast when the regimes change? (iii) Can forecasting robustifications help? The forecast results show that models incorporates economic fundamentals perform better in less regulated periods when the exchange rate can oat more freely. For the forecast experiments with breaks in the forecast origin, the exchange rate CVAR model perform the best before robustifications. In most cases, the intercept-correction and double-difference device improve the forecast performance in both dynamic forecast and one-step forecast. Different models seem to do well under different forecast scenario after applying the robust devices.

JEL Classification: F31, F37, C53
Key words: Exchange rates, Forecasting, US Dollar, Chinese Yuan

1. Introduction

Exchange rate plays a fundamental role in international financial management. Short-term hedging or cash portfolio management decisions often refers to the forecast of the exchange rate movement. In the long term, it is important for the private sectors or governments to make strategic decisions based on the forecast of exchange rate. With the rapid growth of China's economy and fast process of globalizations in last decade, the Chinese Yuan versus US Dollar (USD/CNY) exchange rate has become one of the most important economy index in the world economic markets. Due to the particularity of Chinese economy, the mechanism which determines the USD/CNY exchange rate is different from that for other major exchange rates. The USD/CNY exchange rate exhibits very different pattern in different periods as it changes wildly from one period to another according to the economic reforms and policies

This paper examines and compares some of the frequently used models' ability to forecast the USD/CNY exchange rate to evaluate which classes of models best forecast the USD/CNY exchange rate after the first marketization reform of Chinese exchange rate in July, 2005. In particular, the paper focus in answering the following questions:

(i) Do models' forecast performance change when the marketization level changes?

(ii) Which model has the best forecast when the regimes change?

(iii) How do the forecasts behave after applying robust devices?

In order to answer these questions, six different models are estimated here using the data of USD/CNY exchange rate, China-US interest rate differential, China-US price level differential, Chinese Yuan versus Euro (EUR/CNY) exchange rate and Euro versus US Dollar (USD/EUR) exchange rate. Among all six models, two of them are univariate models: a random walk model and a two-lag autoregressive model. The other four models are multivariate models: three fundamental based vector autoregressive (VAR) models using the exchange rate with the interest rate differentials or price level differentials or both and, lastly, a cointegrated vector autoregressive (C-VAR) model with the USD/CNY, EUR/CNY and ERU/USD exchange rates. From the results, I find that:

(i) In strictly appreciating periods with more market restrictions, simple time series models perform better. However, models incorporate economic fundamentals have better forecast during more volatile periods in recent years as they generally have less forecast bias.

(ii) The robust devices generally improve the forecast performance of all the models. The intercept correction techniques works better in the switching from appreciation channel to peg channel. The double difference device works better in appreciation periods with location shifts.

(iii) The forecast encompassing test result does not point to any given model being very successful for all the forecast scenarios. Different models seem to do well under different forecast scenario.

The rest of the paper is organized as follows. Section 2 briefly summarizes the former literature on forecasting exchange rates and the ones focus on Chinese exchange rate. Section 3 is a brief summary of Chinese foreign exchange rate policy history. Section 4 describes the models used in this paper for forecasting the USD/CNY exchange rate. Section 5 is the data description and the summary of characteristics of the monthly data. Section 6 introduce the forecast scenarios, robust devices, and forecast encompassing test used in this paper. Section 7 presents the forecast results and comparisons between the models. Section 8 concludes.

2. Literature Review

There are literatures trying to predict exchange rate decades ago. Unfortunately, exchange rate are very difficult, if not impossible, to predict empirically, at least in the short horizon. Economic fundamental differences between countries in the area such as interest rate, money growth, inflation and trade balances have long been considered as critical part of determinants for a the countries' currency values. However, what may be correct in theory hasn't been prove easily in the empirical studies. The classic Meese and Rogoff (1983) paper and the some subsequent literature have found that macroeconomic models draw from economic theories cannot beat a random walk in predicting exchange rates in the short run. So known as the "exchange rate determination puzzle." In the Meese and Rogoff (1983)'s finding, the economic fundamentals such as trade balance, money supply and other macro-fundamental variables are not useful in forecasting the exchange rate between countries with similar inflation rates. However, this puzzle is less acute for long-run exchange rate predictions, since there is strong evidence of a closer relationship between exchange rates and fundamentals at longer horizons (Mark, 1995). MacDonald and Taylor (1994) challenge the random walk model by showing that an unrestricted monetary model with some short-term error correction mechanism, can has better predicting performance than the random walk base on the root mean square error. Chinn and Meese (1995) and Mark and Choi (1997) also found that, as in other financial markets, longer horizon changes in the exchange rates are predictable. Engel and West (2005) demonstrate that the lack of forecast ability of exchange rates using fundamentals can be with a rational expectations model. The exchange rate can be view as the discounted present value of expected economic fundamentals.

Although the forecast of exchange rates have more comforting result recently, there is still no strong evidence for a particular type of model can significantly outperform other models for all major exchange rates. Cheung et al. (2005) re-assess exchange rate prediction using a wider set of models that have been proposed in the last decade: interest rate parity, productivity based models, purchasing power parity, the sticky-price monetary model and a composite specification. They concludes that the results do not point to any given model/specification combination as being very successful, some models seem to do well at certain horizons for certain currency.

Besides, most of the exchange rate being forecast in these papers are between US dollar and other developed country currencies. Despite the fact of China being the largest exporting country and the important role USD/CNY exchange rate plays in the global imbalance problem, relatively few studies focus on the USD/CNY exchange rate. Dai et al (2005) use ARIMA and EGARCH models to simulate and forecast the pattern of the daily Chinese exchange rate. The conclusion is that the predicted result of EGARCH model is more fitted than that of ARIMA model and the EGARCH model can describe the dynamic characteristics of RMB exchange rate more appropriately.

3. Chinese Exchange Rate Policy

Prior to August 2005, China basically maintained a US dollar pegged exchange rate system. On July 21, 2005, the People's Bank of China (PBOC) announced a reform of the exchange rate regime which states the Chinese Yuan would become adjustable with reference to exchange rate movements of currencies in a basket. However, unlike a true floating exchange rate, the Chinese Yuan would only have a fluctuation band up to 0.3% on a daily basis against the basket of currencies.

In July 2008, China halted the appreciation trend of the Chinese Yuan because of the occurrence of global financial crisis and its globally negative effect on the demand in Chinese export sectors. During the crisis period, the export declined by more than 15% percent which lead to closure of thousands of factory and unemployment of millions of workers. To prevent this from turning into worse situation, the PBOC intervened to prevent its currency from further appreciating and keep the exchange rate almost constant around 6.8 for two years.

On June 19, 2010, China's central bank made another announcement to "proceed further with reform of the RMB exchange rate regime and to enhance the RMB exchange rate flexibility." It resumed the RMB's steady appreciation against the US dollar through the managed floating exchange rate regime tied to a basket of currencies.

After then, there are several fluctuation band widen activities and a one-time revaluation against US dollar. First on April 16, 2012, the PBOC increased the daily trading band of USD/CNY to 1%. Later on March 17, 2014, the People's Bank of China continued to increase the flexibility of the exchange rate allowing for 2% rise or fall from a daily midpoint rate. More recently, the central bank make a one-time adjustment to the exchange rate which triggered the biggest one-day drop around 2% since 1994. It said the determination of the exchange rate will become more aligned with supply and demand in the market. The evolvement of Chinese exchange rate policy apparently contributes a lot to the formation of the special exchange rate pattern. Different periods' policies are also the main reason for the regime division in later discussion.

4. Exchange Rate Forecasting Models

This section describes the six models used to compute the USD/CNY exchange rate forecasts in this paper. Two of them are univariate models and the remaining four are multi-variate models. The model forms being chosen here is meant to represent the frequently used models in exchange rate estimation and forecast models discussed in the literature above. The models include variables in both levels and first differences, the multi-variate models have different information sets (three different economic fundamental based model) and other restrictions on parameters (cointegration in the C-VAR). All the models are summerized in table 1.

The first model considered is a random walk with drift model (RW). Random walk model remains as a puzzle in the forecast of exchange rates. As mentioned before, Meese and Rogoff (1983) presents the superior out-of-sample forecast performance of the random walk model relative to various competing models. Many subsequent work also demonstrate that univariate time series, unconstrained vector autoregression, and other structure models based primarily on monetary theory fail to beat the naive random walk model in terms of overall prediction accuracy in many different samples. Not surprisingly, it will have a good performance in one-step forecast than many other models due to its special model form, especially when there are structural breaks in the forecast horizons.

$$\Delta e_t = \beta_0 + u_t \tag{1}$$

The AR(2) model of the level of exchange rates (in log transformation). Because of the persistence in the exchange rate series itself, it is natural to consider an autoregressive model with an optimal lag length selection. In this paper, the optimal lag is selected as two base on AIC and SC information criteria. The AR(2) model differs from the random walk model in some aspects: it has a different expected forecast error variance compared to the random walk model. Besides, the AR(2) model can capture the persistence in the growth rate as well. Since the exchange rate exhibits persistence growth rate in some of the sample periods, the AR(2) model may perform well.

The interest rate differential model (ID-VAR) is an unrestricted vector autoregressive model (2 lags) of the USD/CNY exchange rate and interest rate differential between US and China. The theoretical relations between interest rate differential and exchange rate can be characterized as the uncovered interest rate parity (in logs) below in equation (2). It can be transformed into a more general form in equation (3). Additionally, to make this kind of fundamental based model to be comparable to other complete models in this paper, we need to specify the DGP process for the interest rate differential as well. If we add another AR(2) equation as the one in equation (4) for the interest differential which depends on lags of exchange rate and its own lags. This system of equation (3) and (4) becomes an unrestricted VAR model of exchange rate and interest rate differential.

$$E_t(e_{t+1}) - e_t = i_t - i_t^* \tag{2}$$

$$\Delta e_t = \beta_0 + \beta_1 (i - i^*)_{t-1} + \beta_2 \Delta(i - i^*)_{t-1} + \beta_3 e_{t-1} + \beta_4 \Delta e_{t-1} + u_t \tag{3}$$

$$(i - i^*)_t = \beta_0 + \beta_1 (i - i^*)_{t-1} + \beta_2 (i - i^*)_{t-2} + \beta_3 e_{t-1} + \beta_4 e_{t-2} + \mu_t \tag{4}$$

The Purchasing Power Parity fundamental model (PPP-VAR) is built as an unrestricted vector autoregressive model (2 lags) of the USD/CNY exchange rate and price level differential between US and China similarly as the interest differential model. The economic rationale is the change in the nominal exchange rate is a function of its deviation from its fundamental value as in equation (5). Here we build the model base on the Purchasing Power Parity that the exchange rate will adjust over time to eliminate its deviation from long-run PPP. Again, the generalized model is built as an unrestricted VAR(2) model to be comparable to other complete models in this paper.

$$\Delta e_t = \beta_0 + \beta_1 (f_t - e_t) + \mu_t, \qquad f_t = p_t - p_t^* \tag{5}$$

Another unrestricted vector autoregressive model (2 lags) consist of the levels of USD/CNY exchange rates, interest rate differentials and price differentials. This unrestricted VAR generalizes the above interest rate differentials model and PPP fundamental model. This model is built to capture some potential interrelationship among them that can't be captured in the previous two VAR models.

The final model (ER-CVAR) is a cointegrated vector autoregressive model (2 lags) consists of the USD/CNY, EUR/CNY and USD/EUR exchange rates. Not surprisingly, the cointegration is found among these three and the imposed (1; -1; -1) restriction as stated in equation (6) below is accepted.

$$e = eurcny + usdeur \tag{6}$$

5. Data sources and description

$$x_t = (e, i - i^*, p - p^*, cnyeur, usdeur)_t$$

All the level variables used in this paper is monthly data with log transformation. The variable e is the monthly level data of USD/CNY exchange rate; $i - i^*$ and $p - p^*$ are the interest rate differentials and price level differentials between China and the United States. The interest rate in China is represented by the short term discount rate and the interest rate in the U.S. is the Fed Fund rate. All the variables above are obtained from FRED at the St. Louis Fed online database. The $cnyeur$ and the $usdeur$ are the EUR/CNY and USD/EUR nominal exchange rates which are obtained from the European Central Bank online database.

From the level and first difference time series graphs of e_t in figure 1(a) and (b), we could see that the whole sample periods from 2005.7 to 2014.3 can be divided into three separate regimes. Regime I ranges from 2005.7-2008.7, during these regime, the USD/CNY exchange rate keeps appreciating. Regime II ranges from 2008.8-2010.6, the exchange rate is relatively steady in these periods. The remaining periods are categorized as Regime III , the exchange rate is appreciating again in this regime and has some small transitory depreciations as well. Because there is a 5 months' depreciating periods from 2012.3 to 2012.7 that shift the trend upwards, the Regime III is divided into III^a which ranges from 2010.7 to 2012.2 and III^b which ranges from 2012.3-2014.3. The rest of the more recently sample is assigned as Regime III^c. Based on these divisions, a set of dummy variables are defined accordingly. R1, R2 and R3 are three step dummies which equal to one within the corresponding regime. Besides, impulse dummy variables for the whole Regime II and periods of 2012.3-2012.7 are created for the estimation and forecasts, their value is one in its corresponding month and zero elsewhere.

6. Forecast Scenarios, Robust devices and Encompassing Test

6.1 Introduction of Forecast Scenario

In this section, we introduce two sets of forecast comparison among the models. First is a within-regime fixed step forecast comparison for different forecast horizon between strictly appreciating periods with more market restriction before financial crisis and more volatile periods in more recent years. For the appreciating periods, I choose regime I which has more regulation as discuss in the previous section of Chinese exchange rate policy history and the volatile periods I choose the regime III which is less regulated and has both appreciation and depreciation. In figure 1(b), the first difference graph of the exchange rate, we can see the difference between Regime I and Regime III. Regime I is a strictly depreciation period as the exchange rate's first order difference are all negative and even decrease over the regime. Regime 3, however, is more volatile as it has both positive and negative values shown in the exchange rate difference figure. This set of tests is focused on the forecast result without any breaks in the sample.

Secondly, based on the regime divisions, both the dynamic forecasts and one-step forecasts of the models are being conducted under three different forecast scenarios. This second set of tests is to compared the models' performance for both non-robustified and robustified forecast when there are breaks in the forecast origin. The forecast scenarios are summarized as follow:

{II | I}: Estimate the model using information in Regime I and forecast into Regime II. This forecast scenarios correspond to the exchange rate move from appreciation channel into steady channel.

{III^a | II}: Estimate the model using information in Regime II and forecast into Regime III^a. This forecast scenarios correspond to the exchange rate move from steady channel into appreciation channel.

{III^b | (I + III^a)}: Estimate the model using only information from Regime I and Regime III^a and forecast into Regime III^b**.** This forecast scenarios correspond to the exchange rate stay inside the appreciation channel. The models under the this scenario is estimated combing the impulse dummy set of the whole Regime II's periods in order to eliminate the impact of Regime II's exchange rate movement on the estimation.

6.2 Robust Devices

For the robustifications, Intercept Correction (IC) and Double-Difference device (DDD) are introduced as the robust forecast devices in this paper to help improve the forecast result when there are breaks in the forecast origin.

6.2.1 Intercept Correction

For the intercept correction, different types of IC techniques are applied. Since the first and second scenarios are similar in the sense that they are both move from one regime to another. So the robustifications for them are similar Intercept Corrections: add a step dummy variable correspond to the new regime into the equation of the USD/CNY exchange rate. The robustifications for the third forecast scenarios is different from the first two as the exchange rate's appreciation trend is not changed in this forecast horizons. So the robustification here for the third scenario is to add another set of impulse dummy from 2012.3-2012.7 to correct for the temporary depreciation shift. The detailed procedure are listed as follow:

{II | I}: Add the step dummy variable R_2 into the models' exchange rate equation. Estimate the model using information in Regime I and the first three periods in Regime II then forecast the remaining periods in Regime II.

{III^a | II}: Add the step dummy variable R_3 into the models' exchange rate equation. Estimate the model using information in Regime II and the first three periods in Regime III then forecast the remaining periods in Regime III^a.

{III[b] | (I + III[a])}: Add the set of impulse dummy variables of 2012.3-2012.7 into the models' exchange rate equation. Estimate the model using information in Regime I and Regime III[a], including the set of impulse dummy (2012.3-2012.7) then forecast for the rest periods in Regime III[b].

6.2.2 Double-Difference Device

Double-Difference device is also used as a second robust devices. Compared to the intercept correction technique above, it does not require that the breaks are implicitly known to the forecaster. It is a naive forecast devices introduced in Hendry (2006). The basic rational behind this device is the assumption that most economic time series do not continuously accelerate thus entail a zero unconditional expectation of the second difference

$$E[\Delta^2 x_t] = 0 \tag{7}$$

which suggests the following forecasting rule:

$$\Delta \widetilde{x_{(T+1|T)}} = \Delta x_T \tag{8}$$

As states in Hendry (2006), the key to the success of double differencing is that no deterministic terms remain. The second differencing not only removes two unit roots, any intercepts and linear trends but also changes location shifts to blips, and converts breaks in trends to impulses.

6.3 Forecast Encompassing Test

Forecast encompassing tests are useful to evaluate and compare different forecasts. The tests for forecasting encompassing concern whether the one-step forecasts of one model can explain the forecast errors made by another (Clements and Hendry, 1993). When comparing two forecasts, a model forecasts encompass another model if this model has unique information that is useful in forecast where the second model has not. In this paper, the forecast encompassing test of Ericsson's (1993) is selected as the test form to do the forecast encompassing test evaluation. In the Ericsson test, the base equation is presented in equation (9) below.

$$e_{T+n|T+n-1} - \tilde{e}_{T+n|T+n-1} = \beta_0 + \beta_1\left(\hat{e}_{T+n|T+n-1} - \tilde{e}_{T+n|T+n-1}\right) + v_{T+n|T+n-1} \tag{9}$$

The test are perform base on the equation above. The null hypothsis is $\{\beta_1 = 0\}$ which correspond to the statement that $\hat{e}$ contains no useful information that could be used to forecast e that $\tilde{e}$ does not have. By allowing a constant in the equation, it allows the forecasts to be bias but the encompassing test can still be conducted. A rejection of the test indicates that the rival model cotains useful information which the encompassing model can benefit from. A failure to reject the null indicates that there is no unique information in the rival model.

7. Forecast Results and Comparisons

7.1 First set of forecast comparison ---- Fixed step Forecast within regimes

The first set of result are the fixed step ahead forecast comparison for result in strictly appreciating periods: regime I. The models are estimated using data from 2005.7 to 2007.4 and the forecast periods are

2007.5-2008.7. The RMSE result of difference forecast horizons are presented in table 2 and plotted in figure 2 (a). From figure 2(a), we can see that generally the simple time series model, the RW and especially the AR (2) model have relatively lower RMSE as the forecast horizon expands. The models incorporate the economic relations such as the ID, IDPPP model have higher RMSE. The PPP model also have a relatively low RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y} - Y\right)^2} = \left(E\left(\hat{Y} - Y\right)\right)^2 + E\left[\left(\hat{Y} - E\left(\hat{Y}\right)\right)^2\right] = \sqrt{Bias\left(\hat{Y}, Y\right)^2 + Var\left(\hat{Y}\right)} \qquad (10)$$

As shown in the equation (10) above, the RMSE is calculated as the root mean of the squares of the forecast error. Thus the mean square forecast error (MSE) can be decomposed into two parts: the square of the forecast bias (square of the mean of forecast error) $Bias\left(\hat{Y}, Y\right)^2$and the variance of forecast error, $Var(\hat{Y})$. To look into more detailed information, figure 2(b) and 2(c) present the square of forecast bias and the variance of forecast error respectively. The relative order and shapes of the lines are similar to the RMSE in figure 2(a). Figure 2(d) shows the ratios of $Var(\hat{Y})/MSE$ for different models over forecast horizons. For the AR(2) and PPP model, the variance part plays a more dominant role in determining the RMSE, especially when the fixed step h is small. In longer horizons, they all converge to around values between 0.3 and 0.4 which mean the square of forecast bias become the dominant part in RMSE. Figure 2(b)-(d) suggest that the AR PPP and RW perform relatively better than the other models, especially the interest differential model and IDPPP model because they has smaller forecast bias and their variance of the forecast error are small as well. To summarize, in this strictly appreciating periods, both forecast bias and variance contribute a significant part in determining the RSME. In the long run the square of forecast bias dominates the variance of forecast error.

Conducting the same kind of comparison forecast test for regime III. The estimation periods are from 2010.7 to 2013.3 while the forecast periods are from 2013.4 to 2015. The result of RMSEs with respect to different forecast horizons are shown in figure 2(e). All the models forecast has similar RMSE in short-term forecast horizon. But as the horizon expand, the RW and CVAR model now has the higher forecast error while the ID, PPP, IDPPP model which take advantage of the basic economic relations have lower RMSE and their performance is very closed to the AR(2) model.

If we examine closely at their square of forecast bias and variance of forecast error in figure 2(f) and 2(g). The models with relatively better prediction performance (smaller RMSEs) have nearly zero forecast bias and also smaller forecast error variance. The shapes and relative positions of the lines in the RMSEs graph 2(e) are similar to the ones in forecast error variance graph in figure 2(g). Combing with the result in figure 2(h), the variance of forecast error could explain most of the changes in RMSEs for the models that have better performance (AR(2), ID, PPP, IDPPP). This however does not apply for the RW and CVAR model which have a variance/MSE ratio around 0.5.

From the result of first set of forecast experiments performed within the regimes, for both forecast experiments in Regime I and Regime III, models with less forecast bias relative to forecast variance generally perform better. This suggests the difference in the forecast bias is the key here to understand the difference RMSE result of the models here. In strictly appreciating periods with more market restrictions, all models' ratios of forecast variance over mean square errors converge to around 0.4, the simple time series models perform better as they have a relatively lower variance/MSE ratios and also smaller values in both forecast bias part and forecast error variance part. However, in Regime III, models incorporate economic fundamentals have much smaller forecast bias compared to the random walk and CVAR model. Therefore these models have less systematic forecast failure and thus have better forecast during more volatile periods in recent years. Moreover, the more recent sample in R3 with less market restriction allowing both appreciation and depreciation has relatively smaller change in the equilibrium mean. So the EqCM models have a more precise prediction of the mean as the forecast bias part are much smaller and thus better performance in the R3.

7.2 Second set of forecast comparison ---- Breaks in Forecast Origin

7.2.1 Dynamic Forecast: Non-robustification vs. Robustification

First, the dynamic forecast of all the models under all three forecast scenarios are conducted and compared. Figure 3 shows forecast result of non-robustified forecast and robustified forecast. The root mean square forecast errors (RMSE) of the non-robustified forecast and robustified forecast are reported in the table 4. The order of the RMSEs are reported on the left panel of table 6. To standardize the RMSE, the Non-robustification forecast is estimated with a set of impulse dummy variables for the first three periods that correspond to the periods used in the intercept correction.

From the non-robustified forecast graphs in figure 3 (the first two rows of graphs in each sub-figures), there are positive systematic forecast errors in the first forecast scenario, negative systematic forecast error in the second scenario and again positive systematic forecast errors in the third one. Note that the growth rates of the exchange rate change totally in the first and second forecast scenarios when moves into the forecast periods while the growth rate in the third forecast scenario has not changed much after the transitory depreciation periods. After applying the intercept correction for all three scenarios, the first scenario's forecasts go back on track and stay very close to the real values. The second scenario's robustification seems to only work well with the random walk model. The rest of the models still exhibit large systematic forecast errors after applying the intercept correction. The robust devices for the third scenario are successful as well. The newly added impulse dummy set brings the appreciation trend up and close to the real value. The robustified forecasts in third scenario mostly lie inside the confidence intervals.

From the result of RMSEs in table 4, the cointegrated VAR model has the smallest RMSEs in all three non-robustified dynamic forecast. The random walk model (with drift) has the second smallest RMSEs while the three fundamental base VAR models and the AR(2) model have larger RMSEs. After applying the intercept correction and DDD to the models, the RMSEs of all the models in all scenarios drop, especially significant for the first scenario. The order of the RMSEs under the robustified models have now changed as the AR(2) model has the smallest RMSE in the first scenario and RW in the second scenario. For the last forecast scenario, the DDD forecast device has the smallest RMSE.

7.3 One-step Forecast: Non-robustification vs. Robustification

Next, the one-step forecast of all the models under all three forecast scenarios are conducted and compared. Figure 4 shows forecast result of non-robustified forecast and robustified forecast. The root mean square forecast errors (RMSE) of the non-robustified forecast and robustified forecast are reported in the table 5. The order of the RMSEs are reported on the right panel of table 6.

From the non-robustified forecast graphs in figure 4 (the upper graph in each sub-figures), there are positive systematic forecast errors in the first forecast scenario for most models. The cointegrated VAR and random walk model's forecasts lie closely to the real exchange rate values. In figure 4(b), again, the one-step forecast for the random walk model and cointegrated model clearly have the best performance. All other models exhibit significantly systematic forecast errors. In figure 4(b), all the models' one-step forecast in the third scenario are close to each other and the real values. After applying the intercept correction for all three scenarios, the systematic forecast errors in the first scenarios have been solved for most models. For the second scenario, the intercept correction reduce the systematic forecast errors of all the models and move them closer to the real values. For the third one, the effects of robustification are less obvious here since the original forecast error before robustification is already small.

From the result of RMSEs in table 5, the cointegrated VAR model has the smallest RMSEs in all three non-robustified one-step forecast. The random walk model (with drift) has the second smallest RMSEs in the first and second scenarios. The three fundamental base VAR models and the AR(2) model have larger RMSEs. After applying the intercept correction to the models and also adding the result of DDD robust device, the RMSEs of all the models in all scenarios drop. The decrease of RMSE is most significant for the first scenario and less obvious for the second and third scenarios. Again, for difference scenarios, the smallest RMSE models are different. ID-VAR model is the smallest RMSE model for the first scenario while CVAR remains as the smallest RMSE model in the second scenario. The DDD again achieves the smallest RMSE model in the third scenario. Notice that in both dynamic forecast and one-step forecast, the DDD is relatively the best model judging from the RMSE. As discussed in Clements and Hendry (1998, 2011), the DDD will usually have a larger forecast error variance but it will be partially offset by lower parameter estimation uncertainty as it removes any intercepts and linear trends ensuring the absence of deterministic terms. The regime III is more volatile in a sense that it has both appreciation and depreciation while these increasing and decreasing trends are less persistent compared to the other regimes.

7.4 Forecast Encompassing Test Result

In this section, the forecast encompassing tests specified in section 5.3 are conducted for the one-step non-robustified forecast calculated in previous sub-section. Table 7 presents the results of the forecast encompassing tests under all three forecast scenarios.

In the first forecast scenario presented in table 7(a), the RW, AR(2), ID-VAR, PPP-VAR, IDPPP-VAR model are all failed to be encompassed by PPP-VAR and ER-CVAR models and encompassed by other models. The cointegrated VAR model is encompassed by all other models. Intuitively, this is not so consistent with the result in previous sub-section that the cointegrated VAR has the smallest RMSEs. However, by observing the figure 4(a), the forecast path of cointegrated VAR is very different from all other models since the cointegrated VAR is built on a total different economic rational. This may in parts reconcile the results.

In the second scenario's result presented in table 7(b), the random walk model and cointegrated model outperform all other models since they are not encompassed by any other models in this scenario. The result is consistent with the RMSEs' result in table 3.

In table 7(c), the ID-VAR model are encompassed by other models except for IDPPP-VAR model. All other models are encompassed by 3 out of 5 models. So ID-VAR model perform the worst in this scenario. This is consistent with the result that ID model has the largest RMSEs in the one-step forecast.

8. Conclusion

This paper assess the forecast ability of 6 different models under different forecast scenarios using the USD/CNY exchange rate. Upon answering the three research questions in section 1, the answers can be draw from the results in the forecast analysis in section 6.

From the result of first set of forecast experiments performed within the regimes, for both forecast experiments in Regime I and Regime III, models with less forecast bias relative to forecast variance generally perform better. This suggests the difference in the forecast bias is the key here to understand the difference RMSE result of the models here. In strictly appreciating periods with more market restrictions, All models' ratios of forecast variance over mean square errors converge to around 0.4, the simple time series models perform better as they have a relatively lower variance/MSE ratios and also smaller values in both forecast bias part and forecast error variance part. However, in Regime III, models incorporate economic fundamentals have much smaller forecast bias compared to the random walk and CVAR model. Therefore these models have less systematic forecast failure and thus have better forecast during more volatile periods in recent years.

For the second set of forecast comparison with breaks in the forecast origin, the cointegrated VAR model which utilize the cointegrated relationship among the three monthly exchange rates and the random walk model have the best forecast performance in both dynamic forecast and one-step forecast when the regimes change, either from appreciation channel to steady channel or vice versa. After the robustifications, however, the result varies.

The forecasting robust devices adopted in this paper generally improve the forecast performance and reduce the RMSEs of the forecast of the USD/CNY exchange rate. The IC works better in the forecast switching from appreciation channel to peg channel. The DDD works better in appreciation periods with location shifts. Moreover, the results from the forecast encompassing test also suggest that each model contains information that can benefit others among the six models in the one-step forecast for the first and third scenarios. The general results in this paper are consistent with the results in Cheung et al. (2005): there is no strong evidence of any given model being very successful, some models seem to do well at certain horizons for certain currency.

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Tables:

Table 1 Model specifications

Model	Specification	
RW	$e_t = \beta_0 + e_{t-1} + u_t$	
AR (2)	$e_t = \beta_0 + \beta_1 e_{t-1} + \beta_2 e_{t-2} + u_t$	
ID-VAR	$\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},$	$\boldsymbol{Y_t} = (e_t,\ i_t - i_t^*)'$
PPP-VAR	$\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},$	$\boldsymbol{Y_t} = (e_t, p_t - p_t^*)'$
IDPPP-VAR	$\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},$	$\boldsymbol{Y_t} = (e_t,\ i_t - i_t^*,\ p_t - p_t^*)'$
ER-CVAR	$\Delta\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\Delta\boldsymbol{Y_{t-1}} + \boldsymbol{\beta_2}\Delta\boldsymbol{Y_{t-2}} + \boldsymbol{\alpha ECM_{t-1}} + \boldsymbol{u_t},$	
	$\boldsymbol{Y_t} = (e_t, eurcny_t\ \ usdeur_t)'$	$ECM_t = (e - eurcny - usdeur)_t$

Table 2. RMSE of h-step forecast within Regime I (*100)

	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	CVAR
h=1	0.66207	0.40823	1.0105	0.46569	0.96817	0.66604
h=2	1.1786	0.584	2.0817	0.77892	1.8007	1.2415
h=4	2.1806	0.97601	3.7753	1.3872	3.3652	2.356
h=6	3.0041	1.1461	4.5992	1.6333	4.391	3.3053
h=8	3.5393	1.2216	5.0294	1.6647	4.9379	3.9676
h=10	3.8225	1.236	5.1938	1.583	5.149	4.3425
h=12	4.0166	1.3063	5.2859	1.5051	5.2719	4.606

Table 3. RMSE of h-step forecast within Regime III (*100)

	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	CVAR
h=1	0.61265	0.46918	0.46063	0.46432	0.46827	0.49969
h=2	1.1233	0.86275	0.85023	0.85641	0.83763	0.96699
h=4	1.8438	1.3175	1.2889	1.3153	1.2806	1.7287
h=6	2.1423	1.3004	1.2718	1.2939	1.2898	2.021
h=8	2.3912	1.1445	1.1349	1.1328	1.1929	2.1854
h=10	2.8571	1.1749	1.1673	1.167	1.278	2.6135
h=12	3.3673	1.2884	1.2589	1.2864	1.3089	3.1791

Table 4. Dynamic Forecast: Non-Robustification vs. Robustifications (RMSE*100)

	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	CVAR	DDD
			Non-Robustified forecast				
II|I	6.03	23.91	15.97	27.12	19.76	**5.13**	
$\mathrm{III^a}$|II	3.46	5.58	5.58	5.55	5.54	**2.98**	
$\mathrm{III^b}$|$(\mathrm{I} + \mathrm{III^a})$	5.04	6.65	6.53	6.56	6.63	**4.57**	
			Robustified forecast				
II|I	0.10	**0.08**	0.61	0.78	0.68	0.61	2.54
III|II	**0.52**	4.51	4.51	4.47	4.45	2.47	2.92
$\mathrm{III^b}$|$(\mathrm{I} + \mathrm{III^a})$	2.42	3.37	3.39	2.85	3.39	1.48	**1.37**

Table 5. One-step Forecast: Non-Robustification vs. Robustifications (RMSE*100)

	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	CVAR	DDD
			Non-Robustified forecast				
II|I	0.51	1.18	0.90	1.27	0.99	**0.44**	
III|II	0.41	3.53	3.38	3.40	3.15	**0.33**	
$III^b\|(I+III^a)$	0.61	0.56	0.61	0.56	0.60	**0.54**	
			Robustified forecast				
II|I	0.12	0.12	**0.12**	0.16	0.14	0.43	0.23
III|II	0.27	3.13	2.94	2.98	2.71	**0.27**	0.39
$III^b\|(I+III^a)$	0.58	0.54	0.59	0.52	0.57	0.46	**0.39**

Table 6. Forecast comparison base on RMSE

	Dynamic Forecast	One-step Forecast
	Non-Robustified forecast	
II|I	CVAR,RW < ID, IDPPP < AR(2),PPP	CVAR,RW < ID, IDPPP <AR(2), PPP
III|II	CVAR,RW < IDPPP ,PPP, ID, AR(2)	CVAR,RW < IDPPP ,PPP, ID, AR(2)
$III^b\|(I+III^a)$	CVAR,RW< ID, PPP, IDPPP, AR(2)	CVAR <PPP <AR(2) < IDPPP < RW < ID
	Robustified forecast	
II|I	AR(2), RW < CVAR, ID, IDPPP, PPP,DDD	ID, RW, AR(2) < IDPPP, PPP < DDD,CVAR
III|II	RW < CVAR,DDD < IDPPP, PPP,ID AR(2)	CVAR, RW,DDD <IDPPP < ID, PPP < AR(2)
$III^b\|(I+III^a)$	DDD,CVAR < RW < ID < AR(2), PPP, IDPPP	DDD<CVAR < PPP < AR(2) < IDPPP, RW, ID

Table7 . Forecast encompassing tests

$$e_{T+n|T+n-1} - \tilde{e}_{T+n|T+n-1} = \beta_0 + \beta_1\left(\hat{e}_{T+n|T+n-1} - \tilde{e}_{T+n|T+n-1}\right) + v_{T+n|T+n-1}$$

Forecast in row denoted $\tilde{e}_{T+n|T+n-1}$. Forecast in column denoted $\hat{e}_{T+n|T+n-1}$

The value in each cell below is the p-value of the restriction $\beta_1 = 0$.

Table 7(a)

Encompassing model	Model to be encompassed					
	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	ER-CVAR
RW		0.003**	0.015**	0.379	0.053*	0.589
AR(2)	0.001**		0.009**	0.613	0.037**	0.621
ID-VAR	0.055*	0.096*		0.347	0.057*	0.726
PPP-VAR	0.002**	0.007**	0.001**		0.006**	0.301
IDPPP-VAR	0.008**	0.017**	0.003**	0.171		0.303
ER-CVAR	0.000**	0.000**	0.000**	0.000**	0.000**	

Table 7(b)

Encompassing model	Model to be encompassed					
	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	ER-CVAR
RW		0.151	0.146	0.147	0.141	0.641
AR(2)	0.000**		0.000**	0.000**	0.000**	0.000**
ID-VAR	0.000**	0.000**		0.798	0.000**	0.000**
PPP-VAR	0.000**	0.000**	0.878		0.000**	0.000**
IDPPP-VAR	0.000**	0.000**	0.000**	0.000**		0.000**
ER-CVAR	0.393	0.265	0.252	0.251	0.236	

Table 7(c)

Encompassing model	Model to be encompassed					
	RW	AR(2)	ID-VAR	PPP-VAR	IDPPP-VAR	ER-CVAR
RW		0.000**	0.186	0.000**	0.126	0.007**
AR(2)	0.000**		0.000**	0.235	0.000**	0.294
ID-VAR	0.088*	0.000**		0.000**	0.534	0.031**
PPP-VAR	0.000**	0.309	0.000**		0.000**	0.341
IDPPP-VAR	0.034**	0.000**	0.244	0.243		0.016**
ER-CVAR	0.000**	0.731	0.000**	0.583	0.000**	

*:significance at 10%. **significance at 5%

Figures:

Figure 1 (a) : USD/CNY exchange rate in levels

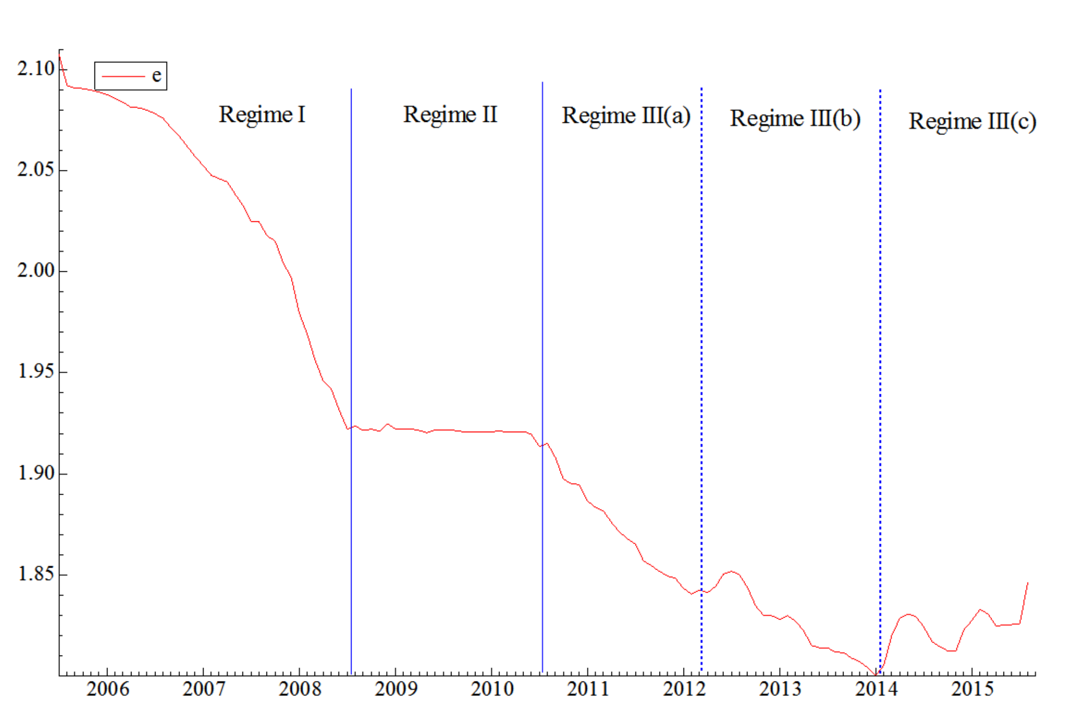


Figure 1 (b): USD/CNY exchange rate in 1st difference

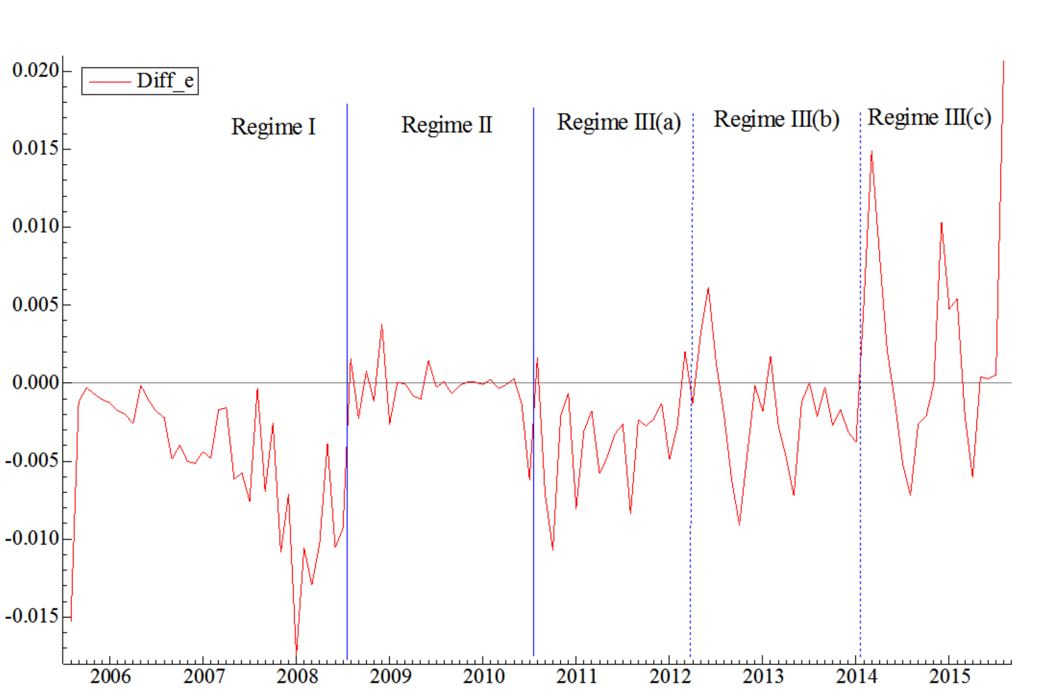


Figure 1 (c) – Other variables in levels

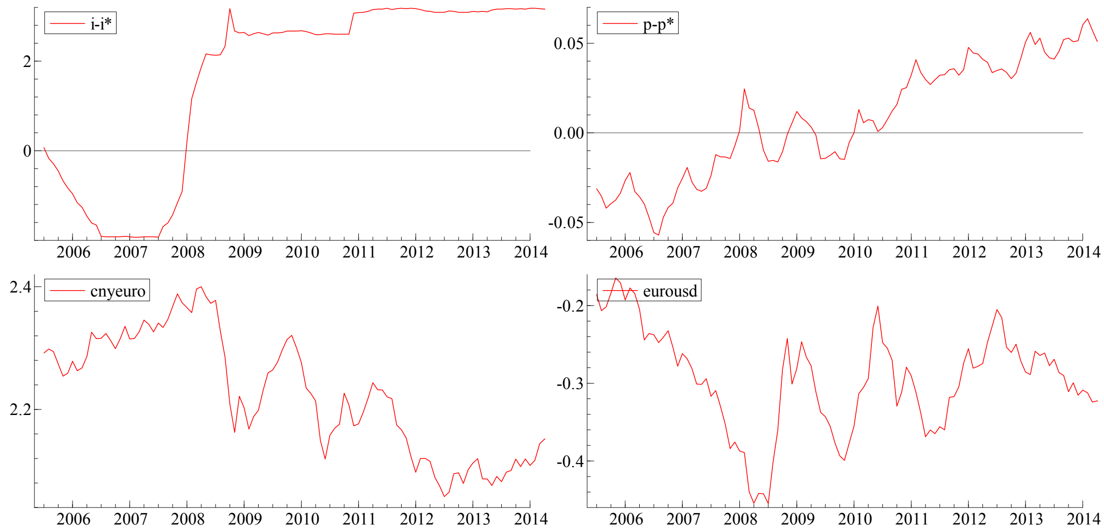


Figure 2 (a): Fixed Step Forecast within Regime I

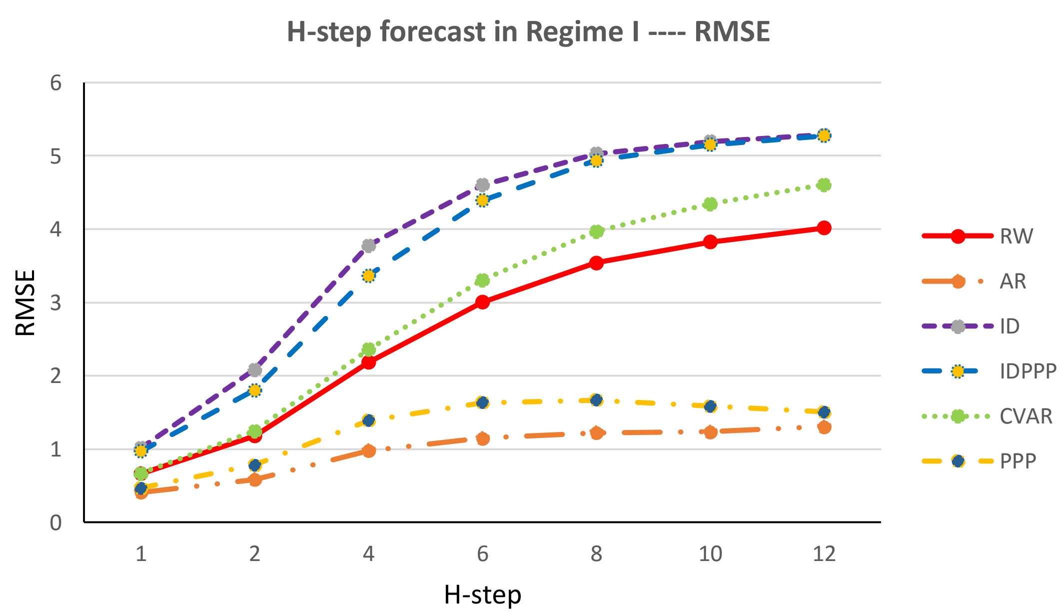


Figure 2(b): Fixed Step Forecast within Regime I

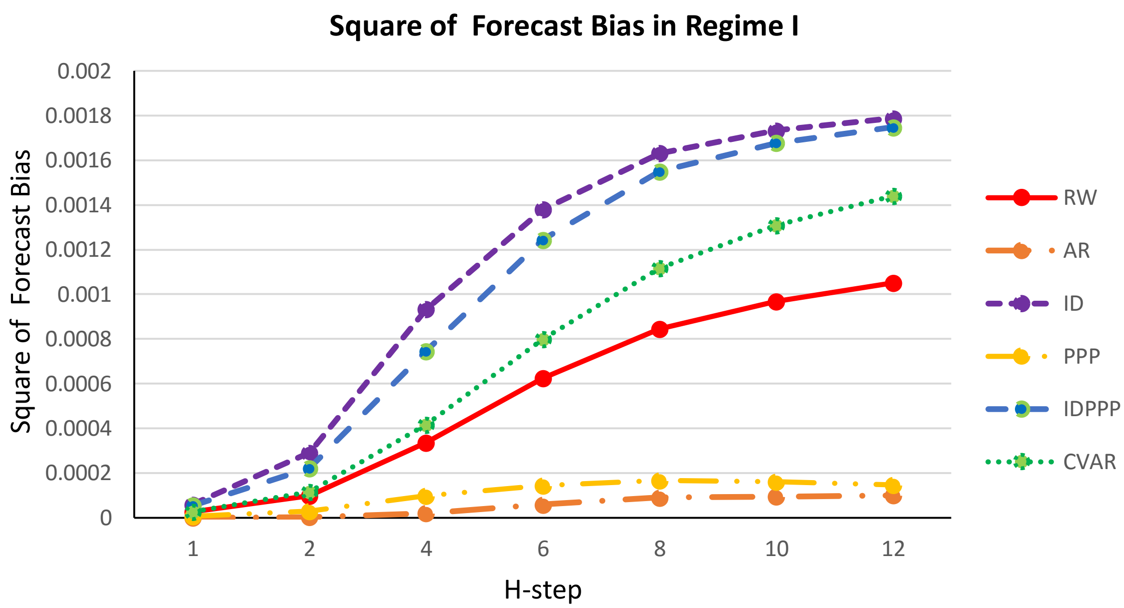


Figure 2 (c): Fixed Step Forecast within Regime I

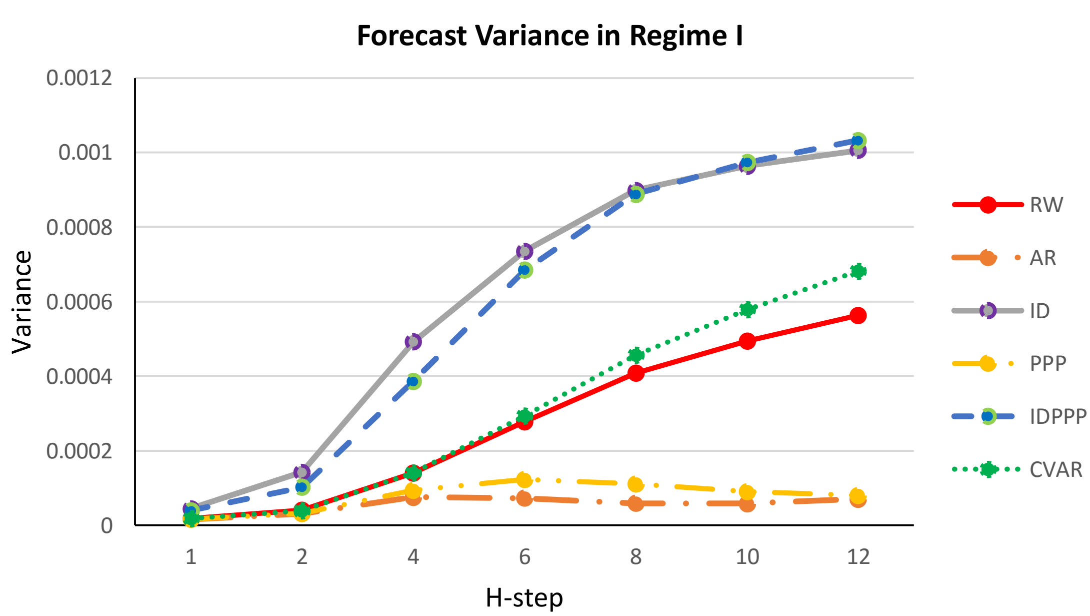


Figure 2 (d): Fixed Step Forecast within Regime I

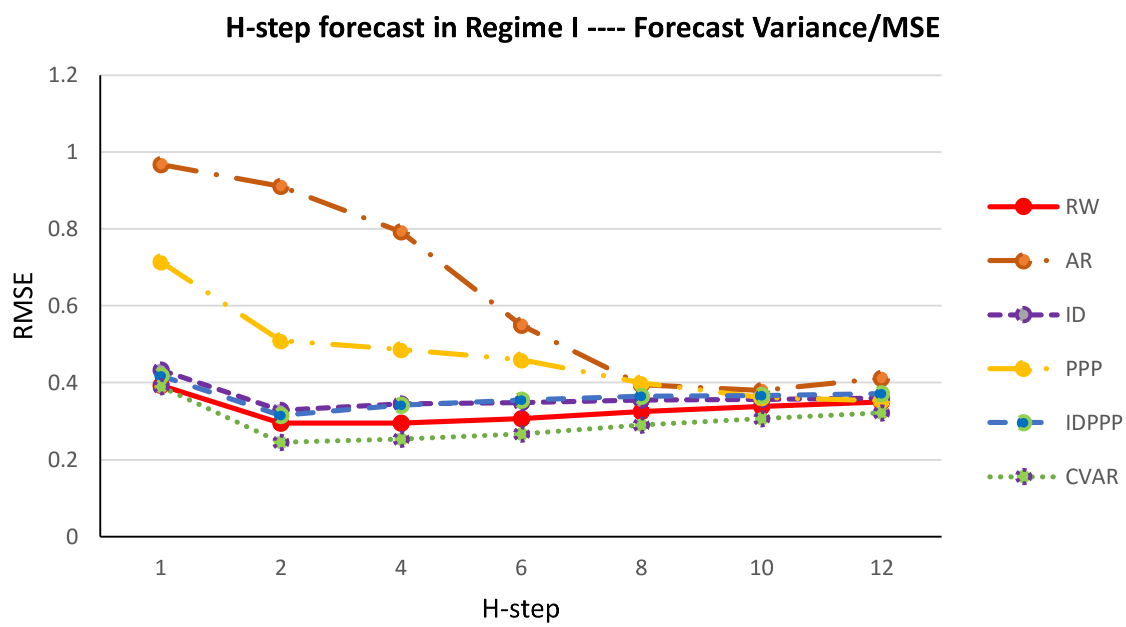


Figure 2 (e): Fixed Step Forecast within Regime III

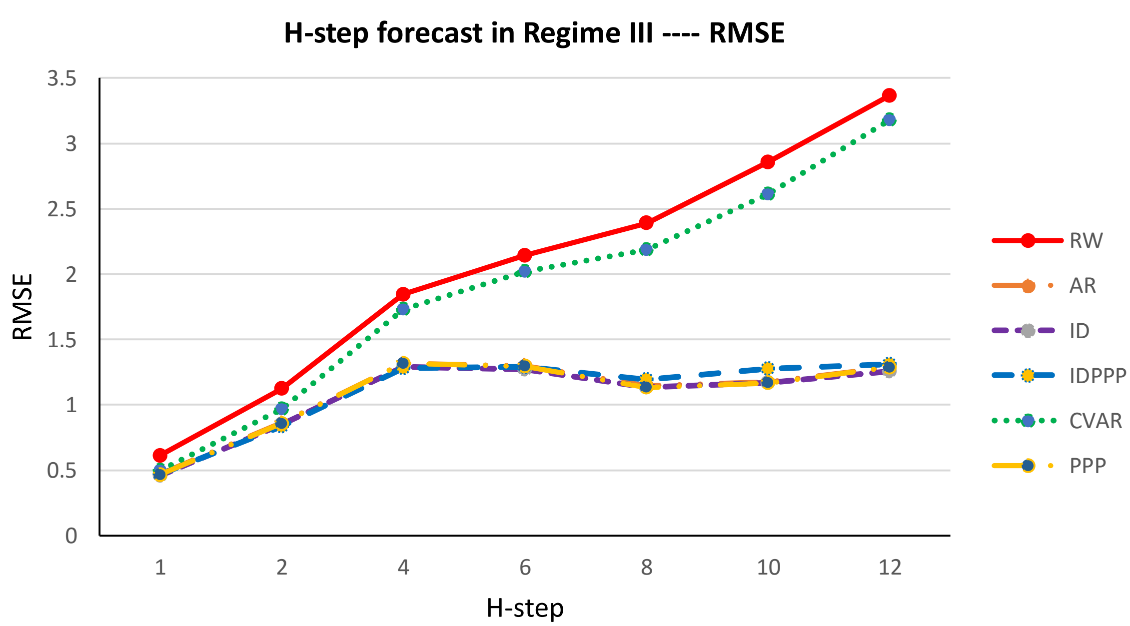


Figure 2 (f): Fixed Step Forecast within Regime III

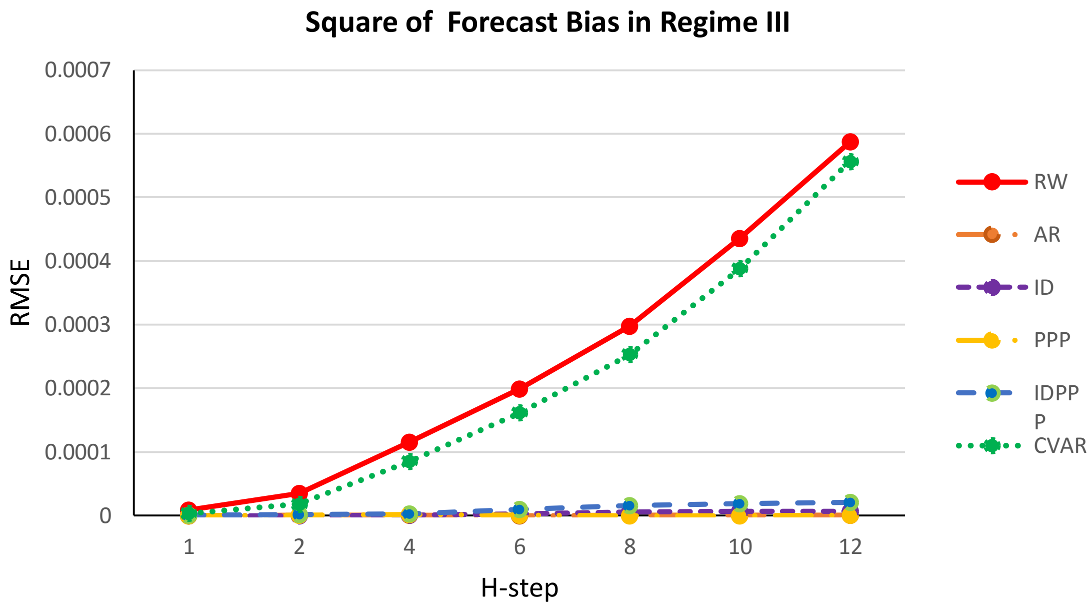


Figure 2 (g): Fixed Step Forecast within Regime III

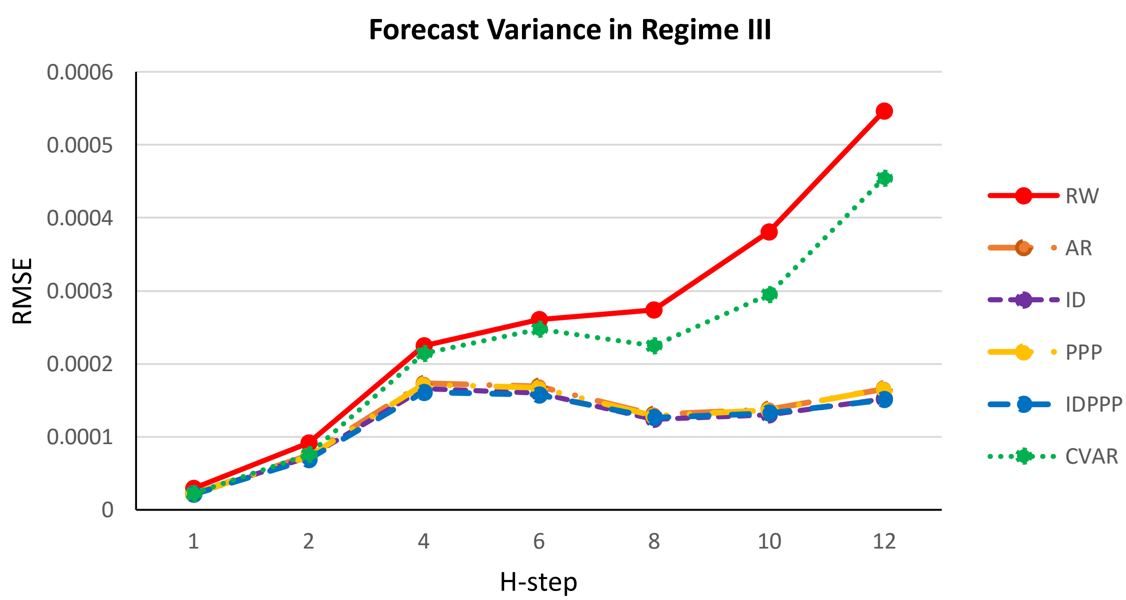


Figure 2 (h): Fixed Step Forecast within Regime III

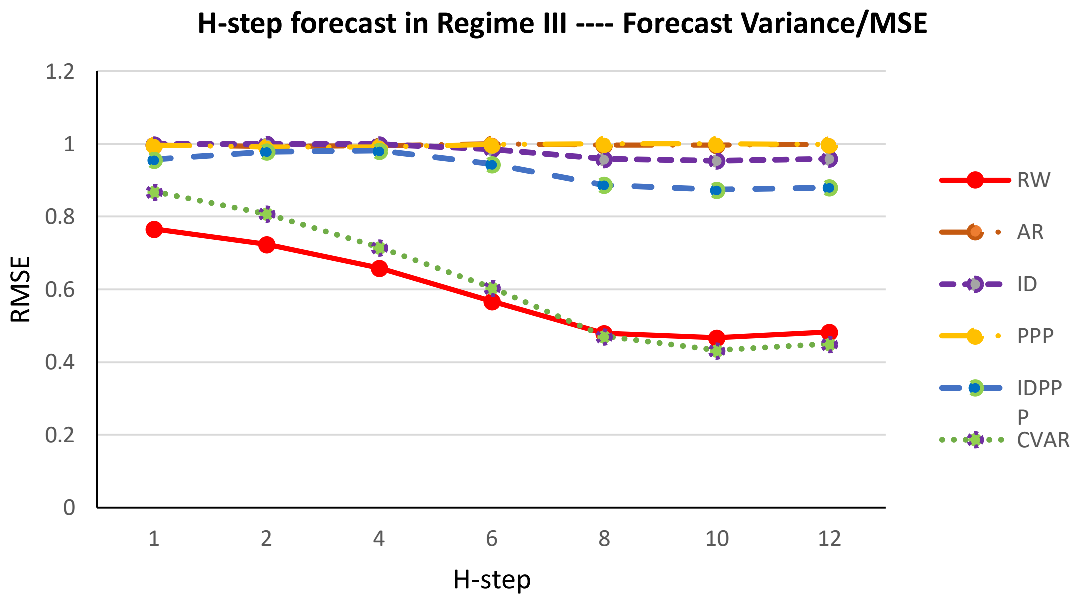


Figure 3.(a): {II | I} Dynamic Forecast (Non-Robustification vs. Robustifications)

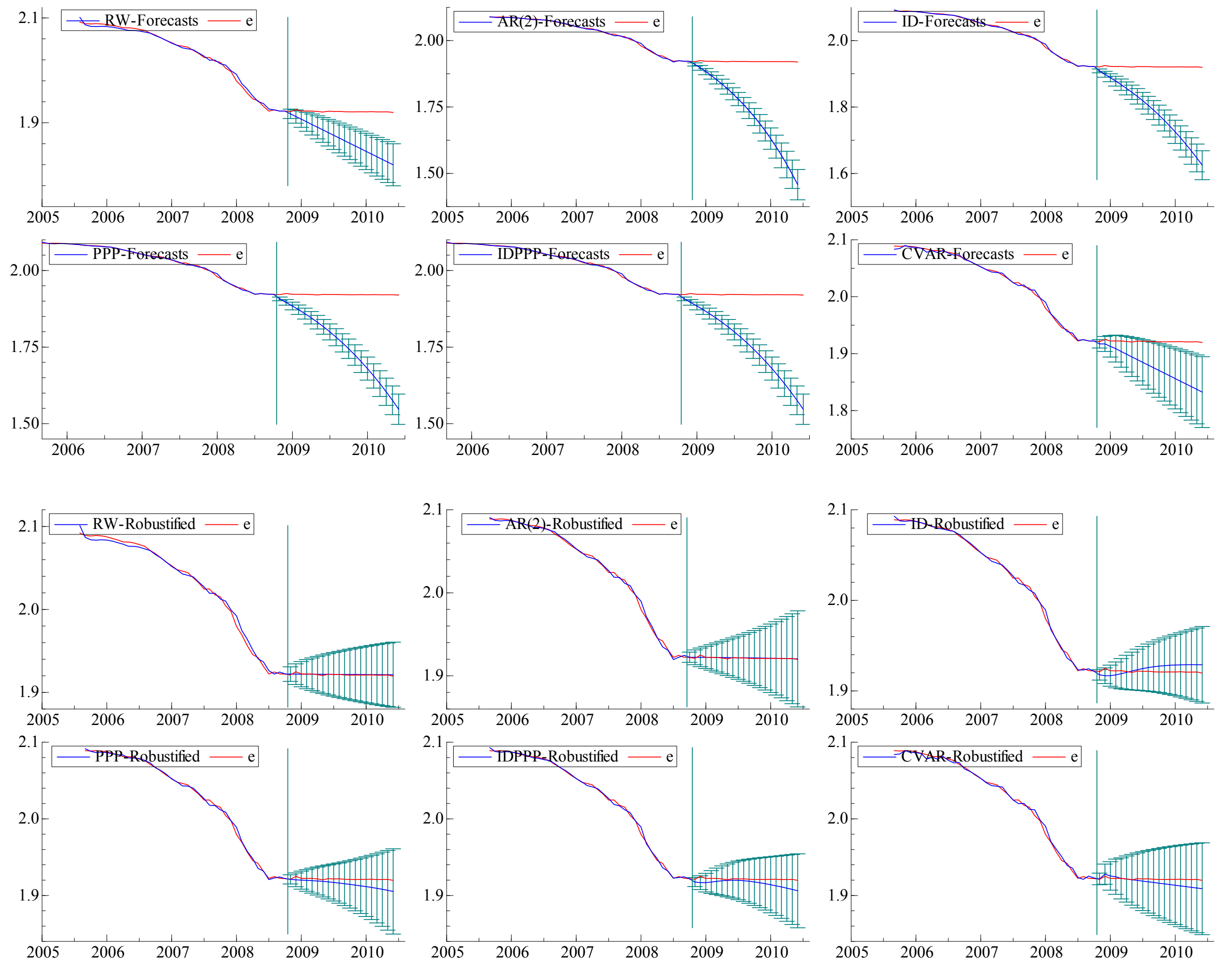


Figure 3(b): {III[a] | II} Dynamic Forecast (Non-Robustification vs. Robustifications)

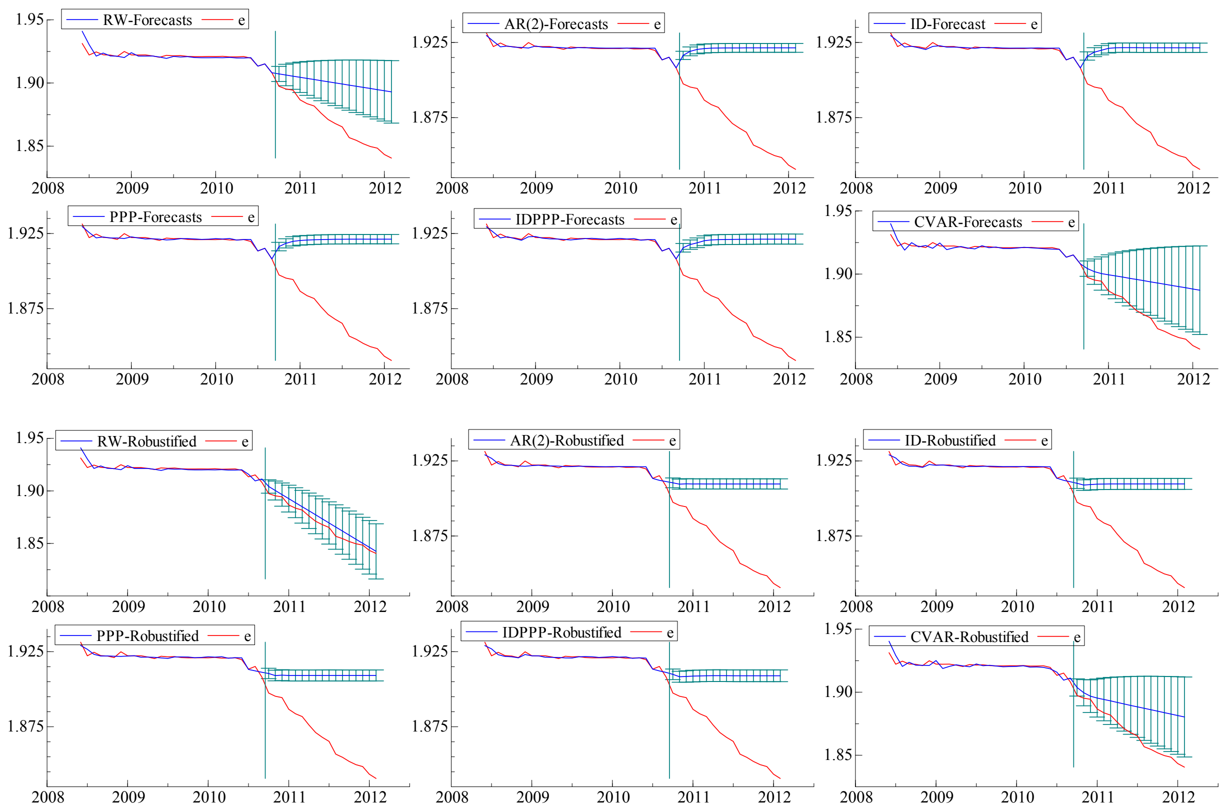


Figure 3 (c): $\{III^b \mid (I + III^a)\}$ Dynamic Forecast (Non-Robustification vs. Robustifications)

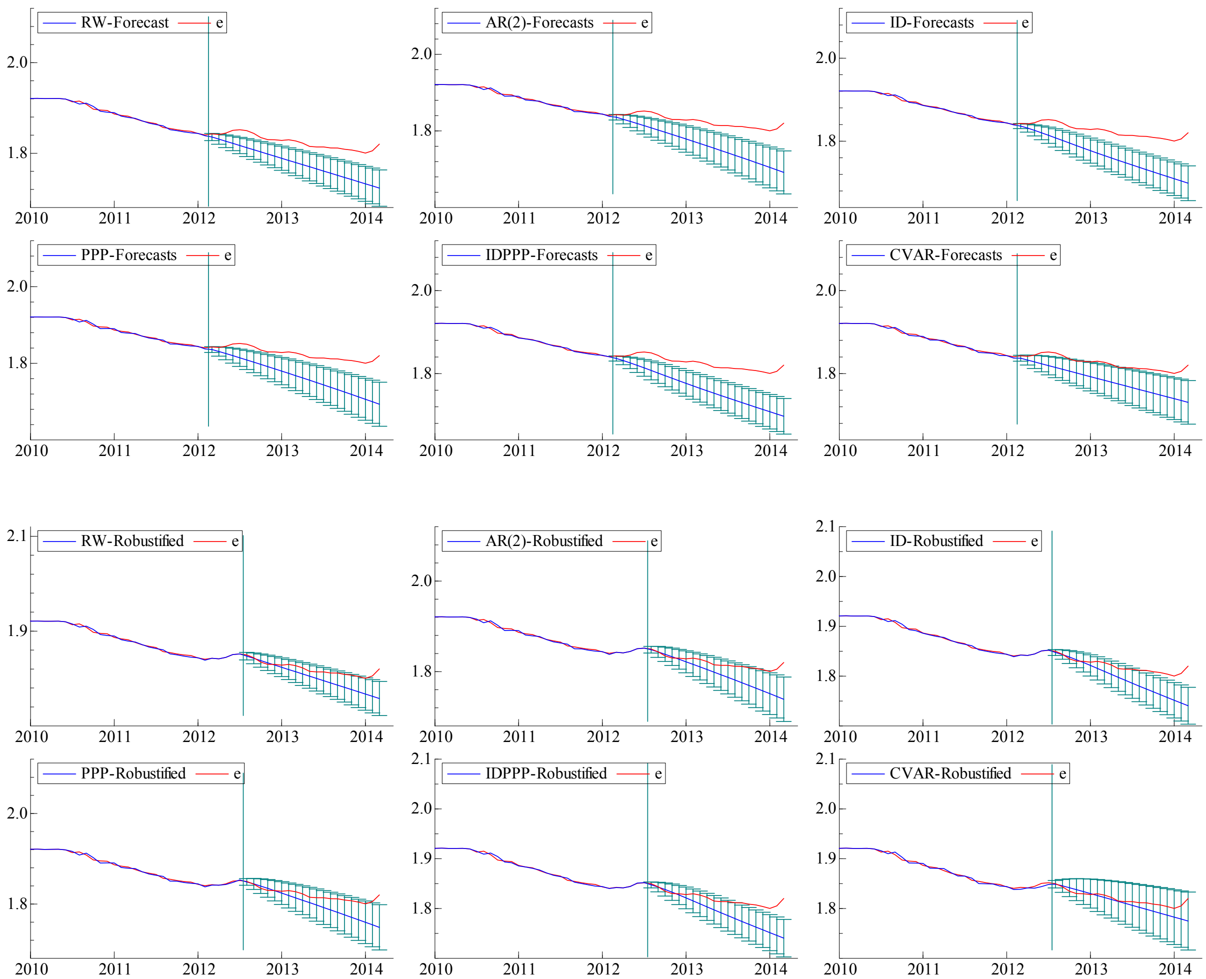
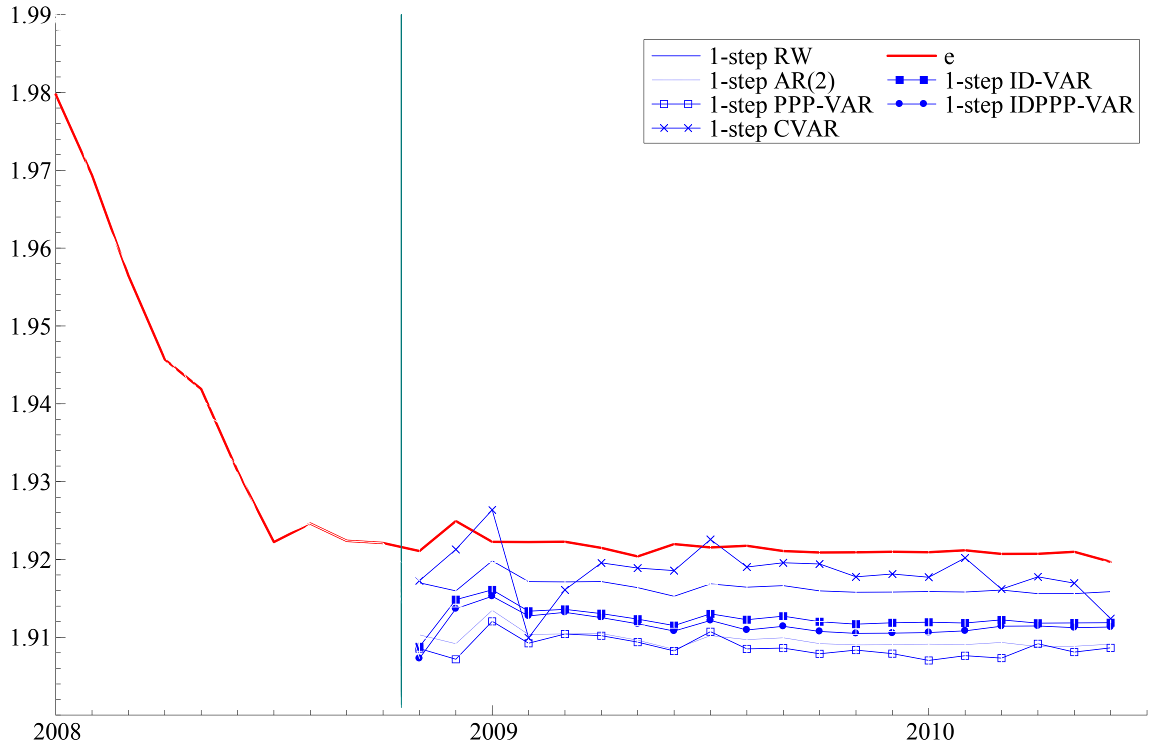


Figure 4(a): {II | I} One-step forecast (Non-Robustification vs. Robustifications)



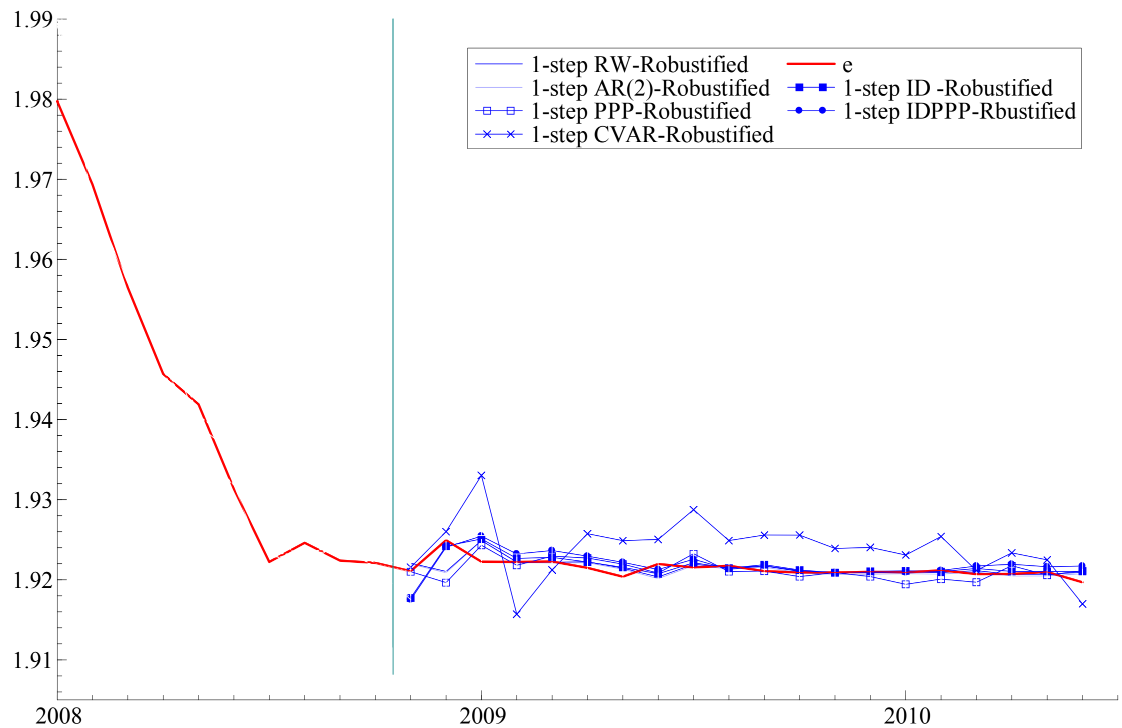


Figure 4 (b): {III[a] | II} One-step forecast (Non-Robustification vs. Robustifications)

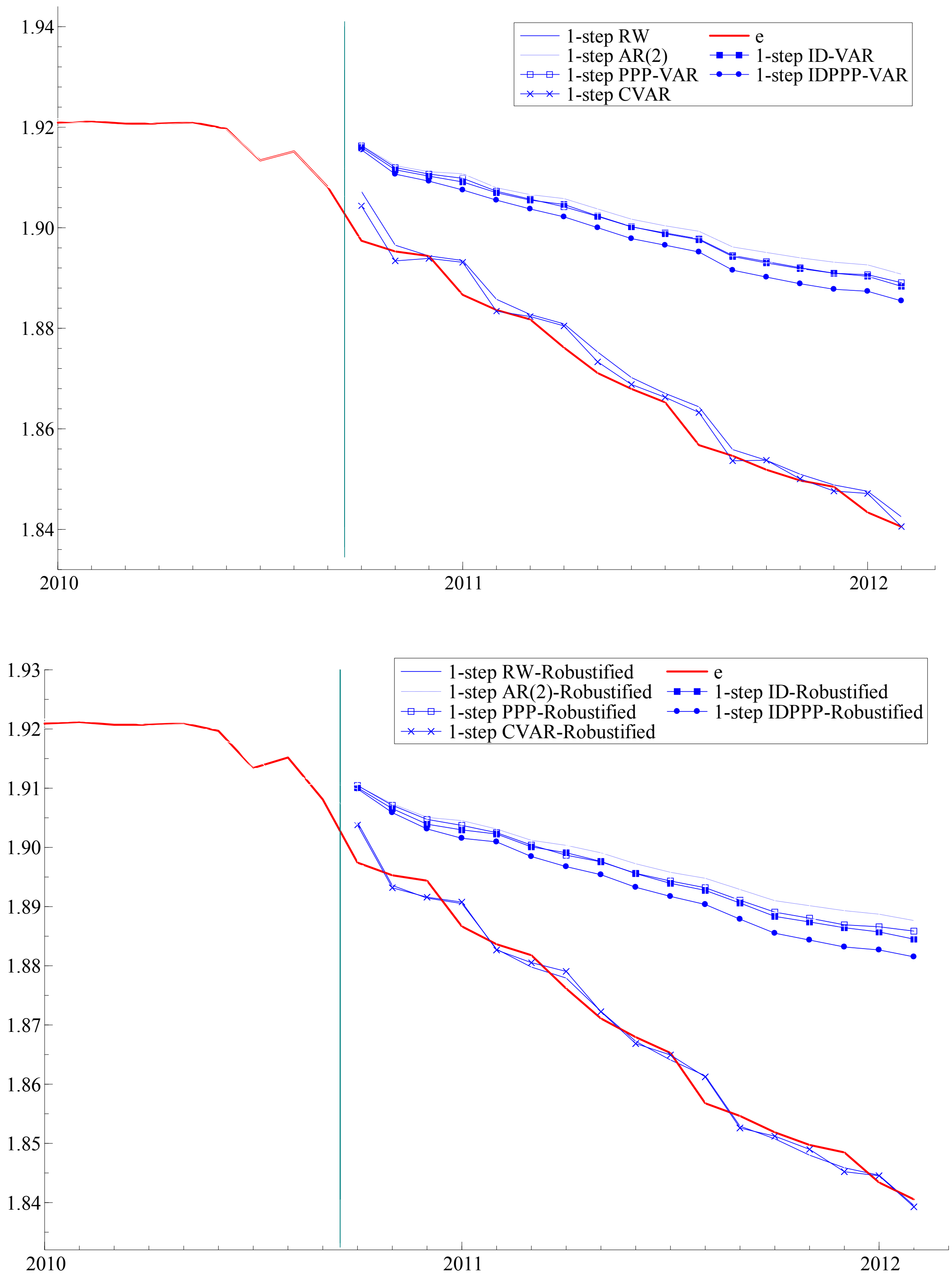
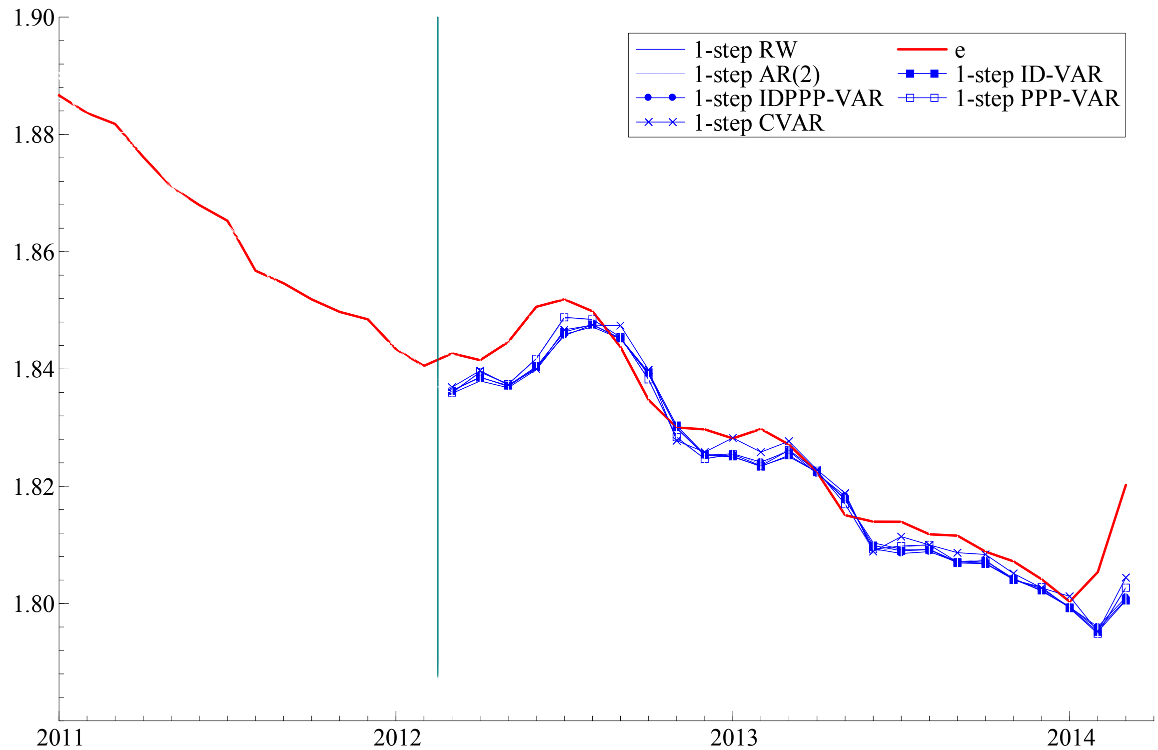
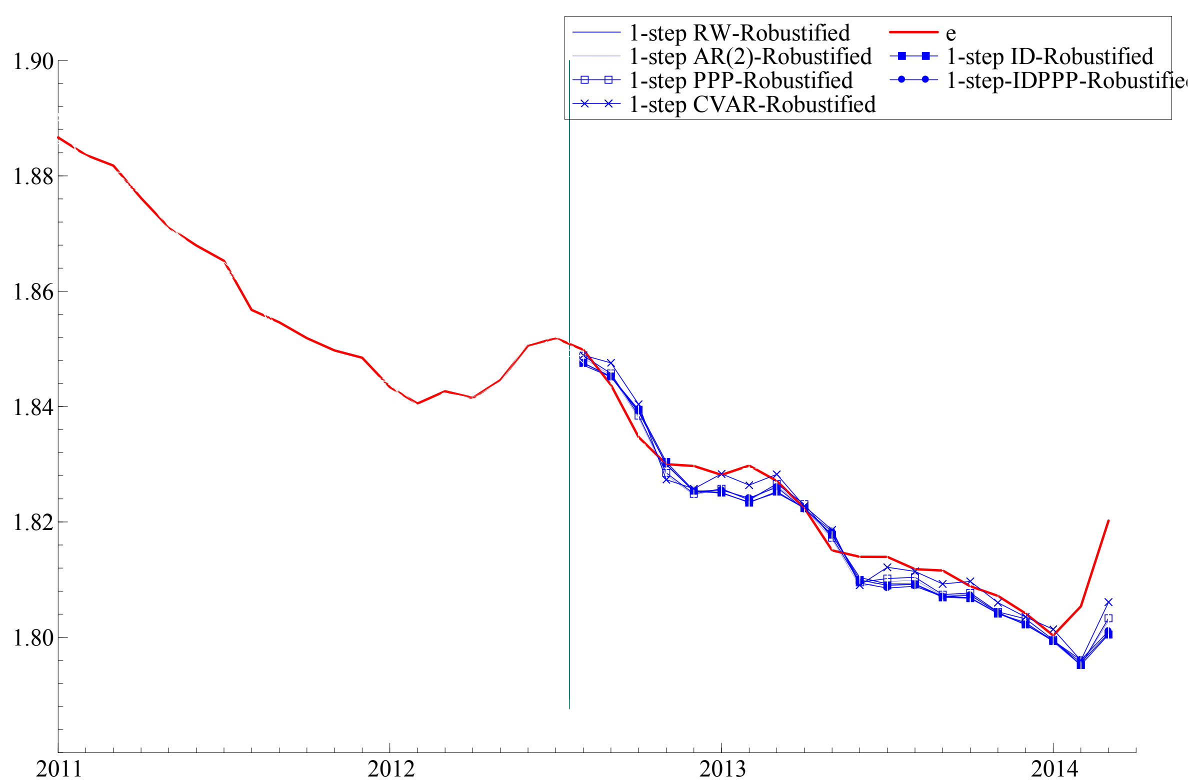


Figure 4 (c): {III^{b} | (I + III^{a})} One-step forecast (Non-Robustification vs. Robustifications)





Appendix

Estimations of first set of forecast comparison: h-step forecast within regimes

Random walk with drift: $\Delta e_t = \beta_0 + u_t$

	R1	R3
β_0	-0.002** (0.0007)	-0.002** (0.0006)
Sigma	0.003	0.003
log-likelihood	90.991	138.416
SEM-AR 1-3 test:	0.10438 [0.9014]	1.4504 [0.2486]
Normality test:	27.617 [0.0000]**	0.76039 [0.6837]
Hetero test:	20.814 [0.0000]**	0.55890 [0.5777]
Hetero-X test:	20.814 [0.0000]**	0.55890 [0.5777]

AR(2) $e_t = \beta_0 + \beta_1 e_{t-1} + \beta_2 e_{t-2} + u_t$

	R1	R3
β_0	-0.122** (0.046)	0.083 (0.042)
β_1	1.134** (0.102)	1.151** (0.175)
β_2	-0.075 (0.102)	-0.197 (0.168)
Sigma	0.001	0.003
log-likelihood	103.683	141.819
AR 1-2 test:	5.0789 [0.0207]*	0.80369 [0.5028]
ARCH 1-2 test	0.51554 [0.6068]	0.10603 [0.9558]
Normality test:	0.025931 [0.9871]	0.42230 [0.8097]
Hetero test:	2.4953 [0.0872]	0.93074 [0.4603]
Hetero-X test:	2.3019 [0.1006]	0.75557 [0.5895]
RESET23 test	16.135 [0.0002]**	0.12060 [0.8868]

ID-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},\qquad \boldsymbol{Y_t} = (e_t,\ i_t - i_t^*)'$

	R1		R3	
	e_t	$(i-i^*)_t$	e_t	$(i-i^*)_t$
β_0	0.131*	5.373	0.123	1.054
	(0.066)	(3.805)	(0.083)	(2.032)
$\beta_1: e_{t-1}$	1.113**	-9.645*	1.168**	1.856
	(0.072)	(4.143)	(0.180)	(4.378)
$\beta_2: e_{t-2}$	-0.177*	6.947	-0.229	-2.120
	(0.076)	(4.376)	(0.168)	(4.081)
$\beta_1: (i-i^*)_{t-1}$	-0.010*	0.765**	-0.014*	0.842**
	(0.004)	(0.237)	(0.007)	(0.188)
$\beta_2: (i-i^*)_{t-2}$	0.011**	0.162	0.009	-0.021
	(0.004)	(0.229)	(0.008)	(0.197)
Sigma	0.001	0.059	0.003	0.082
log-likelihood	145.04		182.191	
Vector AR 1-2 test	0.90668 [0.5302]		1.2520 [0.2823]	
Vector Normality test	4.2029 [0.3792]		86.365 [0.0000]**	
Vector Hetero test	1.3217 [0.2434]		1.4596 [0.1168]	
Vector Hetero-X test	-		2.5537 [0.0010]**	
Vector RESET23 test	2.1889 [0.0743]		7.4294 [0.0000]**	

PPP-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},\qquad \boldsymbol{Y_t} = (e_t, p_t - p_t^*)'$

	R1		R3	
	e_t	$(p-p^*)_t$	e_t	$(p-p^*)_t$
β_0	-0.131**	0.076	1.15**	0.278
	(0.039)	(0.182)	(0.182)	(0.103)
$\beta_1: e_{t-1}$	1.140**	0.165	1.158**	-0.230
	(0.084)	(0.384)	(0.182)	(0.205)
$\beta_2: e_{t-2}$	-0.076	-0.207	-0.202	0.088
	(0.083)	(0.381)	(0.182)	(0.205)
$\beta_1: (p-p^*)_{t-1}$	-0.029	1.261**	0.045	0.961**
	(0.047)	(0.218)	(0.143)	(0.161)
$\beta_2: (p-p^*)_{t-2}$	0.112*	-0.579**	-0.041	-0.400*
	(0.046)	(0.212)	(0.147)	(0.165)
Sigma	0.001	0.005	0.004	0.004
log-likelihood	189.372		279.878	
Vector AR 1-2 test	1.7699 [0.1433]		0.79704 [0.6510]	
Vector Normality test	5.2144 [0.2660]		3.6923 [0.4492]	
Vector Hetero test	1.6645 [0.1033]		0.90600 [0.5933]	
Vector Hetero-X test	-		0.64352 [0.9261]	
Vector RESET23 test	3.0697 [0.0199]*		0.82633 [0.5839]	

IDPPP-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},$ $\boldsymbol{Y_t} = (e_t,\ i_t - i_t^*,\ p_t - p_t^*)'$

	R1			R3		
	e_t	$(i-i^*)_t$	$(p - p^*)_t$	e_t	$(i-i^*)_t$	$(p-p^*)_t$
β_0	0.092 (0.088)	11.725* (4.683)	0.397 (0.450)	0.078 (0.099)	-0.896 (2.319)	0.3149** (0.109)
e_{t-1}	1.110** (0.072)	-10.446** (3.828)	0.201 (0.368)	1.137** (0.191)	1.627 (4.462)	-0.261 (0.210)
e_{t-2}	-0.154 (0.077)	4.650 (4.092)	-0.394 (0.393)	-0.170 (0.186)	-0.793 (4.346)	0.094 (0.205)
$(p-p^*)_{t-1}$	-0.045 (0.042)	0.417 (2.253)	1.136** (0.216)	0.053 (0.139)	4.883 (3.261)	0.943** (0.153)
$(p-p^*)_{t-2}$	0.068 (0.042)	-4.046 (2.262)	-0.567* (0.217)	0.069 (0.166)	-0.839 (3.880)	-0.484* (0.183)
$(i-i^*)_{t-1}$	-0.007 (0.004)	0.595* (0.229)	0.026** (0.022)	-0.016 (0.008)	0.765** (0.197)	0.021* (0.009)
$(i-i^*)_{t-2}$	0.009* (0.004)	0.383 (0.229)	-0.01* (0.022)	0.009 (0.008)	-0.018 (0.195)	-0.016 (0.009)
Sigma	0.001	0.053	0.005	0.003	0.081	0.004
log-likelihood		235.438			325.797	
Vector AR 1-1 test		2.1763 [0.0736]			1.2412 [0.2569]	
Vector Normality test		5.1534 [0.5243]			49.622 [0.0000]**	
Vector Hetero test		0.81465 [0.7308]			1.2029 [0.2044]	
Vector Hetero-X test		-			-	
Vector RESET23 test		2.2906 [0.0605]			2.4475 [0.0064]**	

ER-CVAR: $\Delta \boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \Delta \boldsymbol{Y_{t-1}} + \boldsymbol{\alpha ECM_{t-1}} + \boldsymbol{u_t},$

$\boldsymbol{Y_t} = (e_t, eurcny_t\ \ usdeur_t)'$ $ECM_t = (e - eurcny - usdeur)_t$

	R1			R3		
	Δe_t	$\Delta eurcny_t$	$\Delta usdeur_t$	Δe_t	$\Delta eurcny_t$	$\Delta usdeur_t$
β_0	-0.002** (0.000)	0.002 (0.005)	-0.004 (0.005)	-0.001 (0.001)	-0.001 (0.006)	-0.001 (0.006)
Δe_{t-1}	-0.320 (0.583)	-7.11 (5.571)	6.678 (5.624)	0.420 (0.729)	5.340 (4.067)	-5.087 (4.532)
$\Delta eurcny_{t-1}$	0.458 (0.591)	7.471 (5.648)	-7.032 (5.702)	-0.083 (0.635)	-5.534 (3.546)	5.550 (3.952)
$\Delta usdeur_{t-1}$	0.454 (0.598)	7.495 (5.712)	-7.071 (5.767)	-0.101 (0.652)	-5.637 (3.636)	5.625 (4.052)
ECM_{t-1}	0.545 (0.862)	14.277 (8.23)		-0.112 (1.010)	0.143 (5.634)	0.826 (6.278)
Sigma	0.001	0.017	0.017	0.004	0.021	0.023
log-likelihood		281.120			408.554	
Vector SEM-AR test		1.5332 [0.1928]			1.3199 [0.1949]	
Vector Normality test		6.2028 [0.4009]			0.34742 [0.9992]	
Vector Hetero test:		-			0.96970 [0.5595]	

Estimations of second set of forecast comparison: breaks in forecast origins

Random walk with drift: $\Delta e_t = \beta_0 + u_t$

	{II | I}	{III[a] | II}:	{III[b] | (I + III[a])}
β_0	-0.005** (0.000)	0.001 (0.001)	-0.0047** (0.001)
Sigma	0.005	0.003	0.004
log-likelihood	157.66	125.11	338.02
SEM-AR 1-3 test:	4.7252 [0.0077]**	0.43059 [0.7332]	1.9309 [0.1112]
Normality test:	11.993 [0.0025]**	29.593 [0.0000]**	13.802 [0.0010]**
Hetero test:	0.74767 [0.4813]	78.389 [0.0000]**	0.19314 [0.8251]
Hetero-X test:	0.74767 [0.4813]	78.389 [0.0000]**	-

AR(2) $e_t = \beta_0 + \beta_1 e_{t-1} + \beta_2 e_{t-2} + u_t$

	{II | I}:	{III[a] | II}:	{III[b] | (I + III[a])}
β_0	-0.134** (0.028)	1.149** (0.129)	-0.034** (0.011)
β_1	1.068** (0.136)	0.3871** (0.141)	1.257** (0.124)
β_2	-0.005 (0.144)	0.015 (0.100)	-0.242 (0.139)
Sigma	0.003	0.00132769	0.00382
log-likelihood	170.557	149.126812	294.245
SEM-AR test:	4.1207 [0.0150]*	5.7961 [0.0055]**	1.9502 [0.1100]
Normality test:	20.598 [0.0000]**	19.656 [0.0001]**	20.628 [0.0000]**
Hetero test:	1.6843 [0.1771]	4.3025 [0.0096]**	2.1670 [0.0831]
Hetero-X test:	1.6387 [0.1782]	3.3206 [0.0220]*	-

ID-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t}$, $\boldsymbol{Y_t} = (e_t,\ i_t - i_t^*)'$

	{II | I}:		{III[a] | II}:		{III[b] | (I + III[a])}	
	e_t	$(i-i^*)_t$	e_t	$(i-i^*)_t$	e_t	$(i-i^*)_t$
β_0	-0.111**	3.792*	1.062**	44.407*	-0.052	4.512*
	(0.0351)	(1.63)	(0.170)	(18.63)	(0.031)	(1.815)
$\beta_1: e_{t-1}$	0.965**	-18.615**	0.422**	1.999	1.007**	-15.143*
	(0.149)	(-1.96)	(0.145)	(16.99)	(0.130)	(7.424)
$\beta_2: e_{t-2}$	0.087	16.696	0.024	-23.830	0.016	12.880
	(0.143)	(9.479)	(0.112)	(13.50)	(0.129)	(7.397)
$\beta_1: (i-i^*)_{t-1}$	-0.005	1.429**	-.001	0.194	-0.008**	1.397**
	(0.003)	(0.168)	(0.001)	(0.207)	(0.002)	(0.139)
$\beta_2: (i-i^*)_{t-2}$	0.006**	-0.508**	0.002	-0.127	0.009**	-0.481**
	(0.002)	(0.160)	(0.001)	(0.179)	(0.002)	(0.128)
log-likelihood	194.494		167.478		348.518	
SEM-AR test	1.4123 [0.1950]		-		-	
Normality test	31.841 [0.0000]**		36.723 [0.0000]**		99.035 [0.0000]**	
Hetero test	1.5408 [0.0796]		25.686 [0.0000]**		2.3043 [0.0023]**	

PPP-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t}$, $\boldsymbol{Y_t} = (e_t, p_t - p_t^*)'$

	{II | I}:		{III[a] | II}:		{III[b] | (I + III[a])}	
	e_t	$(p-p^*)_t$	e_t	$(p-p^*)_t$	e_t	$(p-p^*)_t$
β_0	-0.162**	0.119	1.107**	0.415	-0.036	0.217**
	(0.044)	(0.102)	(0.138)	(0.556)	(0.045)	(0.073)
$\beta_1: e_{t-1}$	1.054**	-0.770	0.3808**	0.109	1.256**	-0.502*
	(0.144)	(0.312)	(0.042)	(0.588)	(0.148)	(0.237)
$\beta_2: e_{t-2}$	0.023	0.705	0.017	-0.325	-0.240	0.391
	(0.150)	(0.322)	(0.108)	(0.429)	(0.144)	(0.233)
$\beta_1: (p-p^*)_{t-1}$	-0.107	1.123**	0.041	1.078	-0.037	1.140**
	(0.072)	(0.157)	(0.052)	(0.201)	(0.079)	(0.142)
$\beta_2: (p-p^*)_{t-2}$	0.145*	-0.478**	-0.046	-0.384	0.043	-0.507**
	(0.072)	(0.166)	(0.051)	(0.201)	(0.083)	(0.152)
Sigma	0.003	0.007	0.001		0.004	0.006
log-likelihood	315.480		260.631		556.65	
Vector SEM-AR test	2.3032 [0.0213]*		1.4298 [0.2149]		1.7235 [0.0567]	
Vector Normality test	28.382 [0.0000]**		16.821 [0.0021]**		33.663 [0.0000]**	
Vector Hetero test	2.6769 [0.0006]**		1.9096 [0.0334]*		1.8381 [0.0201]*	
Vector Hetero-X test	3.4248 [0.0000]**		1.3501 [0.2184]		-	

IDPPP-VAR: $\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Y_{t-1}} + \boldsymbol{\beta_2 Y_{t-2}} + \boldsymbol{u_t},\qquad \boldsymbol{Y_t} = (e_t,\ i_t - i_t^*,\ p_t - p_t^*)'$

	{II | I}:			{III[a] | II}:			{III[b] | (I + III[a])}		
	e_t	$(i-i^*)_t$	$(p-p^*)_t$	e_t	$(i-i^*)_t$	$(p-p^*)_t$	e_t	$(i-i^*)_t$	$(p-p^*)_t$
β_0	-0.135**	3.519	0.063	1.007**	40.379	0.101	-0.052	3.857	0.224**
	(0.046)	(3.096)	(0.104)	(0.178)	(21.40)	(0.729)	(0.132)	(2.341)	(0.082)
e_{t-1}	0.975**	-18.715	-0.628	0.440**	3.670	0.052	1.003**	-15.363*	-0.404
	(0.144)	(9.667)	(0.325)	(0.154)	(18.53)	(0.631)	(0.131)	(7.566)	(0.268)
e_{t-2}	0.088	16.945	0.591	0.034	-23.418	-0.116	0.030	13.433	0.289
	(0.146)	(9.780)	(0.328)	(0.119)	(14.29)	(0.486)	(0.121)	(7.583)	(0.265)
$(p-p^*)_{t-1}$	-0.012	-1.435	0.902**	0.026	-2.510	1.003**	0.098	-2.352	1.088**
	(0.085)	(5.907)	(0.191)	(0.057)	(6.214)	(0.225)	(0.070)	(4.711)	(0.157)
$(p-p^*)_{t-2}$	0.057	2.719	-0.232	-0.046	0.894	-0.335	-0.059	3.595	-0.476*
	(0.088)	(5.697)	(0.198)	(0.052)	(6.617)	(0.211)	(0.081)	(4.491)	(0.165)
$(i-i^*)_{t-1}$	-0.005	1.366**	0.010	-0.001	0.1795	0.006	-0.0095**	1.350**	0.004
	(0.003)	(0.213)	(0.007)	(0.001)	(0.221)	(0.007)	(0.002)	(0.157)	(0.005)
$(i-i^*)_{t-2}$	0.005	-0.448*	-0.011	0.002	-0.105	0.001	0.010**	-0.435*	-0.004
	(0.003)	(0.207)	(0.006)	(0.001)	(0.206)	(0.007)	(0.002)	(0.144)	(0.005)
Sigma	0.003	0.187	0.006	0.001	0.164	0.005	0.003	0.183	0.006
log-likelihood	343.600			280.267			617.165		
SEM-AR test	1.3885 [0.1556]			4.1160 [0.0007]**			1.4261 [0.0990]		
Normality test	36.132 [0.0000]**			41.274 [0.0000]**			99.574 [0.0000]**		
Hetero test	1.8452 [0.0024]**			4.4218 [0.0000]**			2.6975 [0.0000]**		

ER-CVAR: $\Delta\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\Delta\boldsymbol{Y_{t-1}} + \boldsymbol{\alpha ECM_{t-1}} + \boldsymbol{u_t},$

$\boldsymbol{Y_t} = (e_t, eurcny_t\ \ usdeur_t)'\qquad ECM_t = (e - eurcny - usdeur)_t$

	{II | I}:			{III[a] | II}:			{III[b] | (I + III[a])}		
	Δe_t	$\Delta eurcny_t$	$\Delta usdeur_t$	Δe_t	$\Delta eurcny_t$	$\Delta usdeur_t$	Δe_t	$\Delta eurcny_t$	$\Delta usdeur_t$
β_0	-0.002**	0.001	-0.004	0.001	-0.007	0.007	-0.003**	0.000	-0.003
	(0.000)	(0.003)	(0.004)	(0.001)	(0.006)	(0.006)	(0.001)	(0.004)	(0.005)
Δe_{t-1}	1.032	-10.385*	11.253**	0.605	5.941	-5.582	0.751	-1.424	2.025
	(1.041)	(4.149)	(4.446)	(0.447)	(4.638)	(4.763)	(0.622)	(3.215)	(3.491)
$\Delta eurcny_{t-1}$	-0.524	10.526*	-10.940**	-0.243	-5.846	5.786	-0.355	1.718	-2.012
	(1.007)	(4.011)	(4.297)	(0.429)	(4.454)	(4.574)	(0.586)	(3.025)	(3.285)
$\Delta usdeur_{t-1}$	-0.575	10.584*	-11.057*	-0.256	-6.093	6.003	-0.404	1.739	-2.088
	(1.016)	(4.049)	(4.339)	(0.435)	(4.515)	(4.637)	(0.596)	(3.081)	(3.346)
ECM_{t-1}	0.699	17.728**	-15.809**	-0.579	2.014	-2.093	-0.348	10.057*	-9.395
	(1.474)	(5.872)	(6.292)	(0.595)	(6.168)	(6.335)	(0.871)	(4.501)	(4.887)
Sigma	0.003	0.015	0.016	0.003	0.031	0.032	0.004	0.018	0.020
log-likelihood	504.760			343.66			1029.678		
SEM-AR test	1.4983 [0.1009]			1.2520 [0.2959]			1.2865 [0.1511]		
Normality test	5.4337 [0.4895]			13.329 [0.0381]*			33.903 [0.0000]**		
Hetero test	1.5042 [0.0260]*			-			1.1860 [0.1400]		