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Résumé de l'article

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Forecasting Exchange Rate in a Large Bayesian VAR Model: The Case of Taiwan

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We study the out-of-sample forecasting performance of 32 exchange rates vis-a-vis the New Taiwan Dollar (NTD) in a 32-variable vector autoregression (VAR) model. The Bayesian approach is applied to the large-scale VAR model (LBVAR), and its (time-varying) forecasting performance is compared to the random-walk model in terms of both forecast accuracy and Giacomini-Rossi fluctuation tests. We find the random-walk model outperforms the LBVAR model in a short-run forecasting competition. Moreover, the dominance of a random-walk in the competition is stable over time. Accordingly, we do not find any benefit of incorporating a rich set of information in predicting the exchange rates vis-a-vis the NTD.

Keywords: Bayesian Approach, Forecast Stability, Vector Autoregression

JEL Classifications: C53, E37, F37

1 Introduction

Understanding the dynamics of the exchange rates is very important to the policymakers living in a small open economy, relying heavily on both exports and imports. Accordingly, quite a lot of the past studies use a variety of models, including either the reduced-form time series regression or the theoretical-based economic models, to forecast the nominal exchange rates. Meese and Rogoff (1983) state that the forecasts of the exchange rate, generated from a simple random-walk setting, are more accurate than those obtained from both the reduced-form and structural exchange rate models.[1] Thus, the random-walk specification of the exchange rate

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[1]The exchange rate models used in Meese and Rogoff (1983) for out-of-sample forecasting competition include the univariate (multivariate) autoregression, the flexible-price and sticky-price monetary models.

becomes a natural competitor to the other models in the exchange rate forecasting competition.[2]

Some studies recently find the benefit of using a large set of relevant information in forecasting macroeconomic indicators, and two types of approaches are particularly adopted by those studies. Stock and Watson (1999, 2002) use the (dynamic) factor analysis, in which a small number of the estimated factors (indexes) are extracted from a large set of time series data, to conduct the macroeconomic forecasting. Instead, Banbura, Giannone and Reichlin (2010) directly bring a large set of variables into the model specification. Specifically, they construct a large-scale Vector autoregression (VAR) model by including 131 macroeconomic indicators. Although the two approaches are essentially different, those studies show the consideration of a large information set helps to forecast the indicators. Accordingly, one of the objectives in this paper is studying whether the use of a rich information set, comprised of a large panel of exchange rates vis-a-vis the New Taiwan Dollar (NTD) only, in a VAR model helps to improve the forecasting performance of the exchange rates than those obtained in the corresponding random-walk frameworks.[3] To the best of our knowledge, this is the first study that applies a Bayesian approach to a large panel of exchange rates vis-a-vis the NTD in a VAR framework for predicting the individual exchange rate. We find that Hsu, Kuan and Lo (2005) and Wu and Chu (2020) forecast (nowcast) Taiwan's economic growth rate by considering a large set of macroeconomic and financial indicators. However, their studies differ from us in the specification of the forecasting framework, the usage of data, the forecasting objective and the estimation approach. More specifically, they apply a factor analysis to a large-scale of macroeconomic and financial data in a non-Bayesian fashion. Tsaih et al. (2018) use big data analytics to predict the daily USD-NTD exchange rate. More specifically, they adopt the data mining approach to transform the huge amount of USD-NTD information, coming from the webpage, social media and forum, into the quantitative data. Then they use machine learning model to construct the link between the exchange rate and its related information. They find the use of rich amount of information correctly identifies the right direction for the movement of the exchange rate with the probability that is higher than 50%. Compare to Tsaih et al. (2018), we estimate a parameter-rich model by directly taking 32 exchange rates vis-a-vis NTD into a VAR model and then generating the forecasts of the exchange rates from it.

Regarding the historical fluctuation of NTD exchange rate, NTD experiences a large appreciation, compared to US Dollar (USD), since 1986 due to the agreement made by Group of

[2] Rossi (2013) states that the toughest competitor to the exchange rate forecasting models is a random-walk without drift.

[3] Carriero, Kapetanios and Marcellino (2009) apply the approach of Bańbura, Giannone, and Reichlin (2010) to a panel of 33 exchange rates vis-a-vis the US Dollar (USD) in a VAR model, and they find both the short-run and long-run forecasting performance of the large-scale VAR model are better than the corresponding random-walk specification. We follow Carriero, Kapetanios and Marcellino (2009) to study the forecasting performance of a panel of 32 exchange rates vis-a-vis the NTD in a large-scale VAR model.

Five (G5) in 1985, the so-called Plaza Accord. More specifically, the exchange of the amount of NTD is decreasing from around 40 NTD per USD in 1985 to 24.62 NTD per USD in 1990. Subsequently, the eruption of Asia financial crisis, occurred in 1997, leads to a substantial depreciation of NTD, pushing it to a higher level that one USD exchanges for around 35 NTD. Afterward the fluctuation of NTD/USD exchange rate is ranging between 28.5 and 35 until now. The occurrence of several events, including the burst of Dot-com bubble in 2001, the global financial crisis and China-US trade war, taken place in the past three decades, leads to a significant depreciation of NTD. Under an unstable environment like this, it is known that the commonly-used test of forecast accuracy, e.g., the Diebold-Mariano test, evaluates the relatively forecasting performance in terms of "average" perspective with a lack of knowledge in whether the forecasting ability of the model changes over time. Rossi (2013, 2021) states that the forecasting ability of the competing models on macroeconomic indicators does change over time. In particular, Rossi (2021) finds the predictive performance of an uncovered interest rate parity (UIRP) in forecasting the growth rate of exchange rate between U.K. pound and USD outperforms the random-walk model before the 1990s. However, the opposite is true since 2000s. Accordingly, using the conventional test for "relative" forecasting ability fails to consider the instability of the macroeconomic and financial indicators. Thus, another objective in this paper is studying the forecasting ability of the two competing models in predicting a large panel of exchange rate vis-a-vis the NTD over time in the presence of the unstable economic environment. To the best of our knowledge, it is rare in the research of macroeconomic forecasting that evaluates the forecasting ability of the competing models in terms of either a "local" or "rolling window" perspective for Taiwan's economy. We fill this gap in the paper.

In the empirical implementation, we set up a large-scale VAR (LSVAR) model for the exchange rates, in which 32 monthly averages of exchange rates vis-a-vis the NTD are considered, and the corresponding foreign currency are particularly issued by the 32 major trading partners of Taiwan (Please refer to Section 3 for the detailed information). According to the Deviance Information Criterion (DIC), the lag length of the model is set as one. We apply the Bayesian approach to estimate the model, and it particularly helps to solve the "over-parameterization" problem via the "Bayesian shrinkage" in which some of the parameters are shrunk toward zero with the tight prior density.[4] We follow Carriero, Kapetanios and Marcellino (2009) to adopt a Minnesota-type prior, a commonly-used prior for the rich-parameter models, and obtain the posterior estimates for generating exchange rate forecasts. More specifically, we estimate the model in a rolling-sample way and generate the multi-step out-of-sample forecasts for the 32 exchange rates and compare the (time-varying) forecasting performance of a large-scale VAR

[4]For example, given a 20-variable VAR model with the lag length of 4 and no intercepts, the total number of sloping parameters to be estimated is 1,600, far larger than the number of data observations. The use of a Bayesian approach could be adopted to deal with the "over-parameterization" problem via Bayesian shrinkage, tightening some of the parameters toward zero.

with the corresponding random-walk model. Several results are found in this paper. First, we find in short-run forecasting competition that the random-walk model outperforms the LSVAR model. However, the forecasting performance of a LSVAR model is comparable to the random-walk model in the long-run. Second, we find in short-run that there is no reverse change in the forecasting ability of the competing models in predicting 32 monthly averages of exchange rates vis-a-vis the NTD. That is, we find the forecasting stability of a random-walk model in predicting the exchange rates. In short, we do not find any benefit of considering a rich set of information that includes a large panel of exchange rates vis-a-vis NTD in predicting the exchange rates.

The reminder of the paper is organized as follows. Section 2 introduces how the Bayesian approach could be applied to a VAR model when the number of variables is large. We describe the source of data and the empirical results in Section 3. Section 4 concludes.

2 Large Bayesian VAR Model

A n-variable vector autoregression (VAR) model with the lag length of p can be represented as

$$y_t = \alpha + A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + \varepsilon_t, \quad t = 1, 2, ..., T, \tag{1}$$

where y_t is a $n \times 1$ vector of endogenous variable; α is a $n \times 1$ vector of intercept; A_j is a $n \times n$ matrix of sloping coefficients, $j = 1, 2, ..., p$; ε_t is a $n \times 1$ vector of *i.i.d.* error term, assumed to follow a multivariate normal density with the zero mean vector and the covariance matrix, Σ. The equation (1) could be rewritten as

$$Y = XB + \Lambda, \tag{2}$$

where the equation (2) is derived by conducting the matrix transposition first and then stacking the observations. In particular, $Y = (y_1, y_2, ..., y_T)^{'}$; $X = \begin{bmatrix} 1 & y_0^{'} & \cdots & y_{1-p}^{'} \\ 1 & y_1^{'} & \cdots & y_{2-p}^{'} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & y_{T-1}^{'} & \cdots & y_{T-p}^{'} \end{bmatrix}$; $\Lambda = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T)^{'}$; $B = \left(\alpha^{'}, A_1^{'}, A_2^{'}, ..., A_p^{'}\right)^{'}$ is a $(1 + np) \times n$ coefficient matrix. In order to explain how to apply the Bayesian approach to the model, we vectorize the matrices shown in equation (2) as

$$y = (I_n \otimes X)\beta + \eta, \tag{3}$$

where $y = vec(Y)$, $\beta = vec(B)$, $\eta = vec(\Lambda)$, and $\eta \sim N(0, \Sigma \otimes I_T)$. According to Bayes' rule, the posterior density of interest, $p(\beta, \Sigma \mid y)$, is expressed as

$$p(\beta, \Sigma \mid y) \propto p(y \mid \beta, \Sigma)\, p(\beta, \Sigma), \tag{4}$$

where $p(y \mid \beta, \Sigma)$ is the likelihood function for the observed data, following a multivariate normal density. $p(\beta, \Sigma)$ is the prior density for the sloping parameters and error covariance matrix, and we particularly assume that it follows a normal-Wishart density, a natural-conjugate prior. Technically speaking, the prior density for the sloping parameter follows a multivariate normal density expressed as

$$\beta \mid \Sigma \sim N\left(\underline{\beta}, \Sigma \otimes \underline{\Phi}\right), \tag{5}$$

where it acts as a Minnesota-type prior in which we impose a priori restrictions on the hyper-parameters $\underline{\beta}$ and $\underline{\Phi}$. More specifically, the prior belief that treats each individual variable as a random-walk process is summarized as follows,

1. Each endogenous variable presents a unit root in its first own lags, and coefficients equal to zero for further lags and cross-variable lag coefficients. Thus, either 0 or 1 is included in $\underline{\beta}$.

2. When the lag is further, we are confident that coefficients linked to this lag have a value of zero. As a result, variance should be smaller as the lag length increases. Moreover, it is assumed that we have little information about the intercept, so that the variance on it should be large. Technically speaking, several values such as λ_1, λ_2, and λ_3 are introduced to implement the Bayesian shrinkage. Please refer to the "Bayesian Estimation, Analysis and Regression (BEAR) Toolbox Technical Guide" for reference (Dieppe, Legrand, and Van Roye, 2018).[5]

Regarding the prior density for the error covariance matrix (Σ), it is assumed to follow an inverse-Wishart density,

$$\Sigma \sim IW\left(\underline{S}, \underline{d}\right), \tag{6}$$

where $\underline{S}$ is a $n \times n$ scale matrix and $\underline{d}$ is the prior degrees of freedom.[6] The above-mentioned Minnesota-type prior for the sloping coefficients and the error covariance matrix, shown in equation (5) and (6), could be implemented in the Bayesian estimation via a different way, the dummy-observation approach (Kadiyala and Karlsson, 1997; Sims and Zha, 1998). More specifically, T_D number of dummy observations Y_D and X_D are generated to match the Minnesota-

[5]We follow the BEAR Toolbox Technical Guide to set the values of λ_1, λ_2, and λ_3.

[6]According to BEAR Toolbox Technical Guide, $\underline{S} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_n^2 \end{bmatrix}$ and $\underline{d} = n + 2$, in which σ_i^2 is the error variance for the endogenous variable i, $i = 1, 2, ..., n$, and it could be estimated by applying the ordinary least squares (OLS) approach to the VAR model.

type prior information, the hyperparameters (moments) shown in equation (5) and (6), as

$$Y_D = \begin{bmatrix} \frac{diag(\rho\sigma_1,\rho\sigma_2,...,\rho\sigma_n)}{\lambda_1} \\ 0_{n(p-1)\times n} \\ 0_{1\times n} \\ diag(\sigma_1,\sigma_2,...,\sigma_n) \end{bmatrix}, \qquad X_D = \begin{bmatrix} \frac{M_p \otimes diag(\sigma_1,\sigma_2,...,\sigma_n)}{\lambda_1} & 0_{np\times 1} \\ 0_{1\times np} & \left(\frac{1}{\lambda_1\lambda_3}\right) \\ 0_{n\times np} & 0_{n\times 1} \end{bmatrix}, \tag{7}$$

where ρ denotes the value of the autoregressive coefficient on the first lags of a VAR model; σ_i is the error standard deviation for the endogenous variable i, $i = 1, .., n$; $M_p = diag\left(1^{\lambda_2}, 2^{\lambda_2}, .., p^{\lambda_2}\right)$; the values of λ_1, λ_2, and λ_3 control the degree of "Bayesian shrinkage".[7] By adding the dummy observations (Y_D, X_D) to the actual ones (Y, X), the equation (2) could be written as

$$Y^* = X^*B + \Lambda^*, \qquad t = 1, 2, ..., T^*, \tag{8}$$

where $Y^* = \left(Y', Y_D'\right)'$, $X^* = \left(X', X_D'\right)'$ and $T^* = T + T_D$. Lastly, the hyperparameters of the posterior density for β and Σ could be obtained by applying the OLS approach to the equation (8). Finally, taking the posterior draws from the above densities are easy since they are well-known densities, and those draws are used to compute the Bayesian point estimates in forecasting exercise.

3 Empirical Data and Results

Regarding the exchange rates vis-a-vis the NTD that we use in the paper, we first collect the monthly averages of NTD-USD exchange rate, expressed as the units of New Taiwan Dollar (NTD) per US Dollar (USD), from Macro Database at the National Statistics (R.O.C.).[8] Based on 32 monthly averages of exchange rates vis-a-vis the USD, collected from IFS (International Financial Statistics) database in International Monetary Fund (IMF), we then transform them into the monthly averages of exchange rates vis-a-vis the NTD, representing the amount of particular foreign currency exchanged for one NTD. For the foreign currencies we consider in the empirical analysis, they are issued by the countries whose are the top 32 trading partners for Taiwan. Table 1 presents the top 32 trading partner for Taiwan, ranked in terms of the total amount of export and import over the sample period between January and August in 2022.[9]

[7]Technically speaking, either the matrix Y_D or X_D could be divided into three parts, corresponding to the "endogenous variables", "exogenous variable (intercept)", and the "error covariance matrix" respectively. Please refer to the BEAR Toolbox Technical Guide for the reference.

[8]In this paper, we use the abbreviation of either "NTD-XXX" or "XXX-NTD" to represent the nominal exchange rate between two currencies. In particular, "NTD" is the domestic currency issued by the central bank of Taiwan and "XXX" refers to the foreign currency.

[9]In Table 1, the number shown in the column of "Total of Trade" could be obtained from the Bureau of Foreign Trade at Ministry of Economic Affairs (R.O.C.). Based on the lowest total of trade for Taiwan-Iran (0.9 billion of US dollars), we finalize a list of 32 foreign countries by additionally picking up the countries whose trade links with Taiwan are higher than 0.9 billion of US dollars from Association of Southeast Asian Nations (ASEAN) and six-countries in South Asia.

The full sample spans from 1999:M1 to 2022:M7, and we choose the year of 1999 as a starting time point because euro is issued at the time. Regarding some of the exchange rates vis-a-vis the USD is missing, they are complementing with those collected from Google Finance.[10] Lastly, we follow Carriero, Kapetanios and Marcellino (2009) to take natural logarithm on all the exchange rates.[11]

We apply the Bayesian approach to a large-scale VAR model with 32 variables, the 32 monthly averages of exchange rates vis-a-vis the NTD. With respect to the lag length selection in the VAR model, we apply the Deviance Information Criterion (DIC), an useful tool for the Bayesian model selection problem, to select the optimal lag length.[12] Table 2 presents the DIC for the VAR model with the different number of lag length, ranging from 1 to 12, and we select the optimal lag length by choosing the one with the smallest DIC value. Thus, we set the lag length for the VAR model as 1. When it comes to the estimation of the parameter, we adopt a Minnesota-type prior, implemented with the use of dummy observation approach, to solve the over-parameterization problem. We take 20,000 draws from the posterior densities and use 10,000 draws to compute the posterior estimates, the point forecasts.[13] We empirically adopt the Bayesian Estimation, Analysis and Regression (BEAR) toolbox proposed by Dieppe, Legrand and Van Roye (2018) to estimate the model in a rolling sample way and generate the one-step-ahead to six-step-ahead out-of-sample forecasts respectively.[14] We repeat the rolling-sample estimation for the random-walk model and obtain the corresponding out-of-sample forecasts from it for the forecasting competition.[15] The forecasting performance of a model is then evaluated relatively in terms of root mean squared forecast error (RMSE) and Diebold-Mariano test. Both Table 3.1 and 3.2 represent the relative RMSE, the ratio of RMSE of a random-walk model to the RMSE of the Bayesian large-scale VAR (LBVAR) model. Thus, if the relative

[10]Below is a list of the nominal exchange rates vis-a-vis the USD is missing for a specific month: Cambodian Riel, 2022:M7; Myanmar Kyat, 2021:M4-2022:M7, Nigerian Naira, 2021:M11-2022:M7, Sri Lankan Rupee, 2021:M3-2022:M7, Vietnamese Dong, 2004:M11 and 2022:M7. Those missing values are complementing with the data collected from Google Finance.

[11]We apply the Bayesian shrinkage via the Minnesota-type prior to solve the "over-parameterization" problem Technically, a prior belief that the individual variables follow random-walk behavior is considered in the prior elicitation of the parameter (Koop and Korobilis, 2010). Since we use level data in a VAR model, the mean vector for the prior density of the parameters includes either "zero" or "one", in which "one" links to the coefficient for the first own lag of the variable and "zero" are set for the remaining coefficients. When the number of lag length increases, the prior density becomes tighter for the corresponding parameters.

[12]Given the posterior density is approximately multivariate normal, the DIC is asymptotically approaching the Akaike Information Criterion (AIC) as the sample size becomes larger.

[13]We discard the first 10,000 draws, the burn-in sample, before the posterior computation.

[14]The first rolling sample spans from 1999:M1 to 2013:M12. We repeat the Bayesian estimation in a rolling sample way for 104 times and the last rolling sample spans from 2007:M8 to 2022:M7.

[15]Using a rolling-sample estimation allows us to test the forecast stability proposed by Giacomini and Rossi (2010).

Table 1

Country Code	Country Currency	Total of Trade
CNY	Chinese Yuan	1421.1
USD	US Dollar	820.2
JPY	Japanese Yen	602.1
EUR	Euro	501.9
HKD	Hong Kong Dollar	461
KRW	Korean Won	398.5
SGD	Singapore Dollar	291.9
MYR	Malaysian Ringgit	213.1
AUD	Australian Dollar	210.5
VND	Vietnamese Dong	152.3
IDR	Indonesia Rupiah	99.4
THB	Thai Baht	96.4
SAR	Saudi Riyal	86.8
PHP	Philippine Peso	72.3
INR	Indian Rupee	59.2
AED	United Arab Emirates Dirham	57.2
KWD	Kuwait Dinar	49.7
MXP	Mexican Peso	46.3
GBP	Great British Pound	45.7
RUB	Russian Ruble	43.2
CAD	Canadian Dollar	42.1
BRC	Brazilian Real	25.5
ZAR	South African Rand	15.8
BDT	Bangladeshi Taka	14.76
NZD	New Zealand Dollar	13.9
TRL	Turkish Lira	13.4
KHR	Cambodian Riel	7.24
PKR	Pakistani Rupee	6.53
NGN	Nigerian Naira	4
LKR	Sri Lankan Rupee	2.88
MMK	Myanmar Kyat	2.02
IRR	Iranian Rial	0.9

Note: the "Total of Trade" shown in the third column is measured in terms of billions of dollars.

RMSE is less than one, then it indicates that a random walk model performs better than the LBVAR. Overall we find a random walk model outperforms the LBVAR model in forecasting the exchange rates. In particular, the one-step-ahead (short-run) forecast errors generated from the LBVAR model in predicting most of the monthly averages of exchange rates vis-a-vis the NTD are significantly larger than those obtained from the corresponding random walk models. However, the forecasting performance of the LBVAR model is comparable to the random walk model when it comes to the long-run exchange rate forecasts. For the top three trading partner of Taiwan, we find a random walk model is dominant in predicting the short-run exchange rates vis-a-vis the NTD, but both random walk and the LBVAR models have the same predictive ability in forecasting the long-run exchange rates, particularly CNY-NTD and USD-NTD.

Table 2. DIC Values in a LBVAR Model

Lag Length	DIC Value
1	**-54257.18**
2	-53233.08
3	-52478.92
4	-52346.14
5	-52431.29
6	-52705.97
7	-52859.38
8	-53058.73
9	-53270.77
10	-53373.31
11	-53424.94
12	-53403.73

Next, we turn to the test of forecast stability of Giacomini and Rossi (2010), the so-called Giacomini-Rossi fluctuation test, measuring the relatively forecasting comparison of two models over time. In particular, we focus on the one-step-ahead rolling forecasts and the results are presented in Table 4.1 to Table 4.10.[16] The two competing models that have significant difference in forecasting performance are represented in bold and italic format when the test of equally predictive ability is conducted on the basis of a full sample. Moreover, the values marked only by bold face are representing that there exists a significant difference of the forecasting performance between two models in a rolling-sample perspective. By taking the forecasts of USD-NTD as an example, when the test statistical values are smaller than -2.56,

[16]We actually find that the main results are the same even we consider applying Giacomini-Rossi fluctuation test to either h-step-ahead rolling forecasts, $h = 2, 3, 4, 5, 6$, or different rolling windows.

Table 3.1. Relative RMSE & Diebold-Mariano (DM) test

	H=1	H=2	H=3		H=1	H=2	H=3
AED	0.8159***	0.8461***	0.8370***	LKR	0.9888	0.9718	0.9839
	(0.0000)	(0.0003)	(0.0058)		(0.6186)	(0.3703)	(0.5736)
AUD	0.7627***	0.6776***	0.6140***	MMK	0.0736*	0.0643*	0.0634*
	(0.0003)	(0.0004)	(0.0004)		(0.0594)	(0.0587)	(0.0552)
BDT	0.7817***	0.7752***	0.7651***	MXP	0.9246***	0.9115*	0.9212
	(0.0019)	(0.0016)	(0.0033)		(0.0034)	(0.0961)	(0.2222)
BRC	0.8637***	0.8353***	0.8245**	MYR	0.8843***	0.8427**	0.8004**
	(0.0064)	(0.0063)	(0.0356)		(0.0010)	(0.0273)	(0.0370)
CAD	0.7748**	0.7234***	0.6950***	NGN	0.8898***	0.9023***	0.8947**
	(0.0116)	(0.0013)	(0.0041)		(0.0007)	(0.0006)	(0.0125)
CNY	0.8230***	0.8317**	0.8320*	NZD	0.8163***	0.7353***	0.6814***
	(0.0048)	(0.0133)	(0.0854)		(0.0016)	(0.0030)	(0.0037)
EUR	0.7261***	0.6695***	0.6367***	PHP	0.8162***	0.7501**	0.7074**
	(0.0000)	(0.0002)	(0.0022)		(0.0029)	(0.0108)	(0.0164)
GBP	0.7777***	0.6964***	0.6324***	PKR	0.9429	0.9537	0.9069
	(0.0001)	(0.0023)	(0.0040)		(0.1733)	(0.6173)	(0.2954)
HKD	0.7934***	0.8236***	0.8120***	RUB	0.8875	0.8244	0.7208
	(0.0000)	(0.0002)	(0.0034)		(0.1220)	(0.2341)	(0.1353)
IDR	0.8007***	0.7125***	0.6547***	SAR	0.8159***	0.8462***	0.8369***
	(0.0002)	(0.0005)	(0.0013)		(0.0000)	(0.0003)	(0.0058)
INR	0.8446***	0.8108**	0.7755**	SGD	0.7518***	0.6989***	0.7012***
	(0.0028)	(0.0152)	(0.0142)		(0.0037)	(0.0058)	(0.0061)
IRR	0.3234**	0.3087**	0.3115**	THB	0.9232	0.9110	0.9421
	(0.0144)	(0.0205)	(0.0280)		(0.1084)	(0.1539)	(0.2984)
JPY	0.7237***	0.6480***	0.6200***	TRL	0.9373	0.9160	0.9136
	(0.0058)	(0.0070)	(0.0076)		(0.2085)	(0.2615)	(0.2834)
KHR	0.8370***	0.8734***	0.8671**	USD	0.8157***	0.8463***	0.8371***
	(0.0020)	(0.0077)	(0.0387)		(0.0000)	(0.0003)	(0.0058)
KRW	0.6091***	0.5962***	0.5789***	VND	0.8056***	0.8056***	0.7737**
	(0.0014)	(0.0002)	(0.0009)		(0.0029)	(0.0047)	(0.0262)
KWD	0.8228***	0.8330***	0.8440**	ZAR	0.8282***	0.7952**	0.7898**
	(0.0001)	(0.0018)	(0.0434)		(0.0007)	(0.0108)	(0.0280)

Note: the values in parentheses are the p-values for the DM test. "", "**" and "***" indicate that the difference of the forecast error generated from two competing models is statistically significant at the significance level of 10%, 5%, and 1% respectively.*

Table 3.2. Relative RMSE & Diebold-Mariano (DM) test

	H=4	H=5	H=6		H=4	H=5	H=6
AED	0.8709	0.8691	0.8353	LKR	1.0412	1.0350	1.0189
	(0.1005)	(0.1812)	(0.1146)		(0.5182)	(0.6044)	(0.7803)
AUD	0.5678***	0.5413***	0.5187***	MMK	0.0759***	0.0995***	0.1037***
	(0.0002)	(0.0001)	(0.0001)		(0.0078)	(0.0000)	(0.0000)
BDT	0.8129***	0.7819**	0.7380***	MXP	0.9182	0.9252	0.9145
	(0.0069)	(0.0101)	(0.0040)		(0.2541)	(0.3579)	(0.3346)
BRC	0.8211*	0.7991*	0.7935	MYR	0.7733**	0.7633**	0.7595**
	(0.0842)	(0.0925)	(0.1013)		(0.0385)	(0.0320)	(0.0223)
CAD	0.6461***	0.6024***	0.5588***	NGN	0.8986	0.9000	0.9019
	(0.0076)	(0.0067)	(0.0094)		(0.1230)	(0.2938)	(0.4386)
CNY	0.8375	0.8174	0.7916*	NZD	0.6217***	0.5689***	0.5250***
	(0.1716)	(0.1399)	(0.0974)		(0.0038)	(0.0028)	(0.0037)
EUR	0.5927***	0.5647**	0.5429**	PHP	0.7103**	0.6787**	0.6701**
	(0.0043)	(0.0160)	(0.0389)		(0.0366)	(0.0192)	(0.0149)
GBP	0.5956***	0.5979***	0.5939***	PKR	0.9147	0.8884	0.8901
	(0.0040)	(0.0031)	(0.0033)		(0.5108)	(0.4091)	(0.5088)
HKD	0.8332**	0.8286*	0.7947**	RUB	0.6708	0.6044	0.5502
	(0.0355)	(0.0745)	(0.0370)		(0.1830)	(0.1817)	(0.2105)
IDR	0.6130**	0.5995**	0.6089**	SAR	0.8708	0.8690	0.8353
	(0.0124)	(0.0250)	(0.0498)		(0.1001)	(0.1808)	(0.1147)
INR	0.7578**	0.7591**	0.7503*	SGD	0.6891***	0.6867***	0.6824***
	(0.0201)	(0.0443)	(0.0597)		(0.0035)	(0.0013)	(0.0013)
IRR	0.3275**	0.3340**	0.3397**	THB	0.9344	0.9554	0.9618
	(0.0322)	(0.0345)	(0.0413)		(0.2248)	(0.4432)	(0.4804)
JPY	0.5951**	0.5662**	0.5424**	TRL	0.9368	0.9265	0.9188
	(0.0117)	(0.0229)	(0.0224)		(0.4835)	(0.3975)	(0.3738)
KHR	0.8986	0.9331	0.9278	USD	0.8709	0.8691	0.8352
	(0.2078)	(0.5164)	(0.5457)		(0.1005)	(0.1814)	(0.1144)
KRW	0.5577***	0.5293***	0.5055***	VND	0.8334**	0.8072**	0.7702***
	(0.0007)	(0.0008)	(0.0008)		(0.0329)	(0.0119)	(0.0036)
KWD	0.8701	0.8630	0.8474	ZAR	0.7842*	0.7483*	0.7304*
	(0.1583)	(0.1711)	(0.1214)		(0.0656)	(0.0606)	(0.0609)

Note: the values in parentheses are the p-values for the DM test. "", "**" and "***" indicate that the difference of the forecast error generated from two competing models is statistically significant at the significance level of 10%, 5%, and 1% respectively.*

Table 4.1. Giacomini-Rossi Fluctuation Test

Time	**LB**	**HB**	***AUD 1 AUD 2***	***BDT 1 BDT 2***	***BRC 1 BRC 2***	***KHR 1 KHR 2***	***CAD 1 CAD 2***	***CNY 1 CNY 2***	***HKD 1 HKD 2***
2019M4	**-2.56**	**2.56**	**-3.21**	-2.24	**-3.10**	-1.76	-2.29	-2.27	-2.27
2019M5	**-2.56**	**2.56**	**-3.22**	-2.08	**-3.15**	-1.80	-2.25	-2.42	-2.26
2019M6	**-2.56**	**2.56**	**-3.22**	-2.24	**-3.08**	-1.79	-2.25	-2.36	-2.24
2019M7	**-2.56**	**2.56**	**-3.40**	-2.31	**-3.04**	-1.83	-2.32	-2.40	-2.24
2019M8	**-2.56**	**2.56**	**-3.35**	-2.31	**-2.94**	-1.82	-2.28	-2.52	-2.26
2019M9	**-2.56**	**2.56**	**-3.32**	-2.30	**-2.92**	-1.74	-2.27	-2.47	-2.21
2019M10	**-2.56**	**2.56**	**-3.37**	-2.36	**-2.97**	-1.66	-2.26	-2.43	-2.15
2019M11	**-2.56**	**2.56**	**-3.30**	-2.33	**-2.85**	-1.65	-2.22	-2.43	-2.17
2019M12	**-2.56**	**2.56**	**-3.41**	-2.36	**-2.97**	-1.67	-2.27	-2.43	-2.15
2020M1	**-2.56**	**2.56**	**-3.12**	-2.35	**-2.80**	-1.70	-2.20	-2.43	-2.12
2020M2	**-2.56**	**2.56**	**-2.98**	-2.37	**-2.80**	-1.69	-2.18	-2.46	-2.15
2020M3	**-2.56**	**2.56**	**-2.98**	-2.30	**-2.57**	-1.53	-2.07	-2.30	-1.98
2020M4	**-2.56**	**2.56**	**-3.34**	-2.41	-2.34	-1.82	-2.15	-2.51	-2.20
2020M5	**-2.56**	**2.56**	**-3.41**	-2.43	-2.34	-1.82	-2.16	-2.43	-2.18
2020M6	**-2.56**	**2.56**	**-3.30**	-2.43	**-2.72**	-1.80	-2.09	-2.43	-2.10
2020M7	**-2.56**	**2.56**	**-3.47**	-2.44	**-2.97**	-1.77	-2.12	-2.49	-2.06
2020M8	**-2.56**	**2.56**	**-3.45**	-2.54	**-2.96**	-1.41	-2.09	-2.33	-1.73
2020M9	**-2.56**	**2.56**	**-3.13**	-2.47	**-2.71**	-1.38	-2.00	-2.34	-1.75
2020M10	**-2.56**	**2.56**	**-3.06**	-2.52	**-2.72**	-1.41	-2.00	-2.34	-1.85
2020M11	**-2.56**	**2.56**	**-3.28**	-2.46	**-2.88**	-1.44	-2.04	-2.27	-1.97
2020M12	**-2.56**	**2.56**	**-3.27**	**-2.86**	**-2.95**	-1.99	-2.00	-2.24	-2.50

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

the locally forecasting ability of a random walk model, labelled as "USD 2" is superior to the LBVAR model, labelled as "USD 1". The opposite is true when the values are larger than 2.56. We could read some results from the table. First, there is no reverse change in the forecasting ability of the model in predicting 32 monthly averages of exchange rates vis-a-vis the NTD. That is, we usually find that either "the random walk model outperforms the LBVAR" or "both models have equally predictive ability" in locally forecasting competition. Instead, we do not find any evidence that the LBVAR model outperforms a random walk model in forecasting any exchange rates. Accordingly, we find the forecasting stability of a random walk model in predicting all the monthly averages of exchange rates vis-a-vis the NTD. Second, even though

Table 4.2. Giacomini-Rossi Fluctuation Test

Time	LB	HB	***AUD 1*** ***AUD 2***	***BDT 1*** ***BDT 2***	***BRC 1*** ***BRC 2***	***KHR 1*** ***KHR 2***	***CAD 1*** ***CAD 2***	***CNY 1*** ***CNY 2***	***HKD 1*** ***HKD 2***
2021M1	**-2.56**	**2.56**	**-3.23**	**-2.68**	**-3.41**	-1.94	-1.85	-1.84	-2.38
2021M2	**-2.56**	**2.56**	**-3.16**	**-2.72**	**-3.52**	-1.95	-1.71	-1.95	-2.43
2021M3	**-2.56**	**2.56**	**-2.97**	**-2.83**	**-3.20**	-1.92	-1.73	-2.02	-2.37
2021M4	**-2.56**	**2.56**	**-2.84**	**-2.58**	**-3.27**	-1.85	-1.77	-2.05	-2.32
2021M5	**-2.56**	**2.56**	**-2.82**	**-2.61**	**-3.23**	-1.92	-1.74	-2.02	-2.29
2021M6	**-2.56**	**2.56**	**-2.75**	-2.38	**-3.24**	-1.81	-1.77	-1.99	-2.06
2021M7	**-2.56**	**2.56**	**-2.81**	**-2.85**	**-3.11**	-2.06	-1.76	-2.11	-2.35
2021M8	**-2.56**	**2.56**	**-2.74**	**-3.03**	**-3.07**	-2.18	-1.73	-2.21	-2.53
2021M9	**-2.56**	**2.56**	**-2.66**	**-3.07**	**-2.87**	-2.14	-1.71	-2.23	-2.53
2021M10	**-2.56**	**2.56**	**-2.81**	**-3.21**	**-2.77**	-2.14	-1.70	-2.16	**-2.62**
2021M11	**-2.56**	**2.56**	**-3.25**	**-3.12**	-2.50	-2.25	-1.87	-1.90	-2.38
2021M12	**-2.56**	**2.56**	**-3.06**	**-3.10**	-2.48	-2.27	-1.71	-1.77	-2.36
2022M1	**-2.56**	**2.56**	**-2.86**	**-3.11**	-2.47	-2.26	-1.67	-1.82	-2.38
2022M2	**-2.56**	**2.56**	**-3.22**	**-3.02**	-2.46	-2.17	-1.66	-1.87	-2.37
2022M3	**-2.56**	**2.56**	**-3.14**	**-3.13**	-2.40	-2.05	-1.72	-1.98	-2.33
2022M4	**-2.56**	**2.56**	**-3.03**	**-3.11**	-2.38	-2.16	-1.82	-1.69	-2.46
2022M5	**-2.56**	**2.56**	**-3.12**	**-2.81**	-2.21	-2.18	-1.84	-1.46	-2.43
2022M6	**-2.56**	**2.56**	**-2.88**	**-3.06**	-2.36	-2.29	-1.70	-2.04	-2.51
2022M7	**-2.56**	**2.56**	**-2.56**	**-3.17**	-2.41	-2.37	-1.63	-2.21	**-2.65**

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

the short-run (one-step-ahead) forecasting performance of the LBVAR is outperformed by the random walk model from a full-sample perspective, its forecasting performance is comparable to the random walk model in terms of the rolling-sample perspective. For example, the locally forecasting ability of two models does not exists the significant difference in predicting the exchange rates of CAD-NTD, CNY-NTD, INR-NTD, LKR-NTD, KHR-NTD, PKR-NTD, THB-NTD, and USD-NTD (in most cases).

4 Conclusions

Forecasting the exchange rate is very important to the conduction of the monetary policy, and thus many of the past studies use a variety of models to forecast it. As stated in Meese and Rogoff (1983), the exchange rate forecasts generated from a random-walk model are more ac-

Table 4.3. Giacomini-Rossi Fluctuation Test

Time	LB	HB	***EUR 1 EUR 2***	***INR 1 INR 2***	***IDR 1 IDR 2***	***IRR 1 IRR 2***	***JPY 1 JPY 2***	***KWD 1 KWD 2***	***MYR 1 MYR 2***
2019M4	**-2.56**	**2.56**	**-5.56**	-1.72	**-3.35**	**-2.87**	-2.01	-2.26	-1.75
2019M5	**-2.56**	**2.56**	**-5.33**	-1.96	**-3.40**	**-2.85**	-1.89	-2.24	-1.73
2019M6	**-2.56**	**2.56**	**-5.44**	-1.96	**-3.42**	**-2.85**	-1.83	-2.24	-1.71
2019M7	**-2.56**	**2.56**	**-5.20**	-1.91	**-3.59**	**-2.80**	-1.87	-2.24	-1.59
2019M8	**-2.56**	**2.56**	**-5.07**	-1.75	**-3.54**	**-2.64**	-1.83	-2.23	-1.65
2019M9	**-2.56**	**2.56**	**-4.75**	-1.80	**-3.51**	**-2.57**	-1.89	-2.16	-1.59
2019M10	**-2.56**	**2.56**	**-4.70**	-1.68	**-3.18**	**-2.56**	-1.95	-2.14	-1.60
2019M11	**-2.56**	**2.56**	**-4.61**	-1.68	**-3.44**	**-2.56**	-1.96	-2.14	-1.62
2019M12	**-2.56**	**2.56**	**-4.60**	-1.65	**-3.51**	-2.52	-1.99	-2.14	-1.70
2020M1	**-2.56**	**2.56**	**-4.46**	-1.71	**-3.72**	-2.49	-2.03	-2.14	-1.81
2020M2	**-2.56**	**2.56**	**-4.32**	-1.85	**-3.53**	-2.46	-2.06	-2.22	-1.57
2020M3	**-2.56**	**2.56**	**-4.29**	-1.44	-1.90	-2.41	-2.18	-2.24	-1.43
2020M4	**-2.56**	**2.56**	**-4.07**	-1.48	-2.37	-2.33	-2.15	-2.36	-1.41
2020M5	**-2.56**	**2.56**	**-4.33**	-1.52	**-2.85**	-2.16	-2.10	-2.38	-2.16
2020M6	**-2.56**	**2.56**	**-3.94**	-1.51	**-3.01**	-2.11	-2.08	-2.35	-2.14
2020M7	**-2.56**	**2.56**	**-4.35**	-1.67	**-3.07**	-2.11	-2.10	-2.35	-2.14
2020M8	**-2.56**	**2.56**	**-4.44**	-1.77	**-2.96**	-2.12	-2.06	-2.02	-2.29
2020M9	**-2.56**	**2.56**	**-4.23**	-1.71	**-2.70**	-2.09	-1.86	-2.14	-2.15
2020M10	**-2.56**	**2.56**	**-4.17**	-1.65	**-2.73**	-2.08	-1.88	-2.24	-1.90
2020M11	**-2.56**	**2.56**	**-4.36**	-1.71	**-3.06**	-2.07	-1.95	-2.26	-2.00
2020M12	**-2.56**	**2.56**	**-4.37**	-1.74	**-3.10**	-2.07	-2.07	-2.35	-2.04

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

curate than those generated from any other economic models, conditioning on a limited number of economic fundamentals. Some studies recently find the benefit of using a large set of relevant information in forecasting macroeconomic indicators, and thus we study whether the use of a rich information set, comprised of a large panel of exchange rates vis-a-vis the NTD only, in a VAR model helps to improve the forecasting performance in the exchange rates than those obtained in the corresponding random-walk frameworks. We estimate two models in a rolling-sample way and then generate the multi-step out-of-sample forecasts, in which the Bayesian approach is applied to a large-scale VAR (LBVAR) model for solving the "over-parameterization" problem. We evaluate the relatively forecasting performance of two competing models in terms

Table 4.4. Giacomini-Rossi Fluctuation Test

Time	LB	HB	***EUR 1 EUR 2***	***INR 1 INR 2***	***IDR 1 IDR 2***	***IRR 1 IRR 2***	***JPY 1 JPY 2***	***KWD 1 KWD 2***	***MYR 1 MYR 2***
2021M1	**-2.56**	**2.56**	**-3.98**	-1.84	**-3.24**	-2.06	-1.91	-2.13	-2.42
2021M2	**-2.56**	**2.56**	**-4.02**	-1.77	**-2.98**	-2.06	-1.95	-2.17	-2.30
2021M3	**-2.56**	**2.56**	**-3.92**	-1.78	**-2.98**	-2.05	-2.02	-2.12	-2.38
2021M4	**-2.56**	**2.56**	**-3.91**	-1.81	**-2.97**	-2.00	-2.06	-2.18	-2.33
2021M5	**-2.56**	**2.56**	**-3.61**	-1.79	**-2.90**	-1.88	-2.10	-1.63	-2.06
2021M6	**-2.56**	**2.56**	**-3.62**	-1.38	**-2.94**	-1.67	-2.29	-1.62	-2.36
2021M7	**-2.56**	**2.56**	**-3.61**	-1.38	**-2.85**	-1.61	-2.00	**-2.63**	-2.08
2021M8	**-2.56**	**2.56**	**-3.61**	-1.30	**-2.84**	-1.59	-2.14	**-2.87**	-2.15
2021M9	**-2.56**	**2.56**	**-3.59**	-1.24	**-2.83**	-1.56	-2.28	**-2.83**	-2.32
2021M10	**-2.56**	**2.56**	**-3.52**	-1.15	**-2.68**	-1.54	-2.26	**-2.91**	-2.20
2021M11	**-2.56**	**2.56**	**-3.55**	-1.17	**-2.57**	**-3.86**	**-2.87**	**-2.90**	-2.39
2021M12	**-2.56**	**2.56**	**-3.60**	-1.28	-2.45	**-3.62**	**-2.91**	**-2.99**	-2.44
2022M1	**-2.56**	**2.56**	**-3.66**	-1.30	-2.42	**-3.66**	**-2.89**	**-3.06**	-2.47
2022M2	**-2.56**	**2.56**	**-3.62**	-1.30	-2.51	**-3.65**	**-2.80**	**-2.98**	-2.54
2022M3	**-2.56**	**2.56**	**-3.59**	-1.40	-2.51	**-3.67**	**-2.79**	**-2.84**	-2.47
2022M4	**-2.56**	**2.56**	**-3.43**	-1.27	**-2.59**	**-3.88**	**-2.70**	**-2.85**	-2.20
2022M5	**-2.56**	**2.56**	**-3.64**	-1.47	-2.52	**-3.93**	**-2.61**	**-2.98**	-2.31
2022M6	**-2.56**	**2.56**	**-3.50**	-1.50	-2.43	**-3.89**	-2.47	**-3.21**	**-2.66**
2022M7	**-2.56**	**2.56**	**-3.54**	-1.51	-2.39	**-3.83**	-2.32	**-3.33**	**-2.69**

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

of forecast accuracy test, the so-called Diebold-Mariano (DM) test. Moreover, the forecast stabilities of two competing models are studies by applying the Giacomini-Rossi fluctuation test, a rolling-sample DM test.

Several results are found in this paper. First, we find in short-run forecasting competition that the random-walk model outperforms the LBVAR model. However, the forecasting performance of the LBVAR model is comparable to the random-walk model in the long-run. Accordingly, we do not find any benefit of considering a rich set of information that includes a large panel of exchange rates vis-a-vis NTD in predicting 32 monthly averages of exchange rates vis-a-vis the NTD. Second, we find in short-run that there is no reverse change in the forecasting ability of the competing models in predicting the exchange rates. That is, we find the forecasting stability of a random-walk model in predicting the exchange rates.

Table 4.5. Giacomini-Rossi Fluctuation Test

Time	LB	HB	***MXP 1*** ***MXP 2***	***MMK 1*** ***MMK 2***	***NZD 1*** ***NZD 2***	***NGN 1*** ***NGN 2***	PKR 1 PKR 2	RUB 1 RUB 2
2019M4	**-2.56**	**2.56**	**-3.76**	**-3.52**	**-2.62**	-2.23	-1.68	-1.98
2019M5	**-2.56**	**2.56**	**-3.83**	**-3.49**	**-2.63**	-2.21	-1.72	-1.94
2019M6	**-2.56**	**2.56**	**-3.84**	**-3.45**	**-2.69**	-2.23	-1.32	-1.94
2019M7	**-2.56**	**2.56**	**-3.97**	**-3.49**	**-2.81**	-2.23	-1.88	-1.93
2019M8	**-2.56**	**2.56**	**-3.81**	**-3.48**	**-2.65**	-2.23	-2.03	-1.95
2019M9	**-2.56**	**2.56**	**-4.06**	**-3.44**	**-2.59**	-2.27	-2.00	-1.94
2019M10	**-2.56**	**2.56**	**-4.06**	**-3.41**	**-2.62**	-2.24	-1.92	-1.94
2019M11	**-2.56**	**2.56**	**-3.97**	**-3.42**	-2.55	-2.26	-1.98	-1.95
2019M12	**-2.56**	**2.56**	**-4.06**	**-3.45**	**-2.60**	-2.25	-1.83	-1.96
2020M1	**-2.56**	**2.56**	**-3.98**	**-3.58**	-2.21	-2.24	-1.88	-1.92
2020M2	**-2.56**	**2.56**	**-3.77**	**-3.64**	-2.10	-2.29	-1.87	-1.80
2020M3	**-2.56**	**2.56**	-2.14	**-3.72**	-2.06	-2.38	-1.62	-1.82
2020M4	**-2.56**	**2.56**	**-2.57**	**-3.78**	-2.06	-2.42	-1.58	-2.01
2020M5	**-2.56**	**2.56**	**-2.73**	**-3.85**	-2.14	-2.48	-1.49	-1.94
2020M6	**-2.56**	**2.56**	**-2.73**	**-3.87**	-1.93	-2.48	-0.81	**-2.84**
2020M7	**-2.56**	**2.56**	**-2.68**	**-3.82**	-2.07	-2.55	-0.80	**-2.76**
2020M8	**-2.56**	**2.56**	**-2.67**	**-3.81**	-2.07	-2.45	-0.87	**-3.17**
2020M9	**-2.56**	**2.56**	-2.50	**-3.81**	-1.87	-2.51	-0.89	**-2.94**
2020M10	**-2.56**	**2.56**	-2.48	**-3.79**	-1.92	-2.54	-1.03	**-2.88**
2020M11	**-2.56**	**2.56**	**-2.59**	**-3.75**	-2.18	**-2.64**	-0.96	**-2.86**
2020M12	**-2.56**	**2.56**	**-2.57**	**-3.78**	-2.21	**-2.79**	-0.96	**-3.04**

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

Table 4.6. Giacomini-Rossi Fluctuation Test

Time	**LB**	**HB**	***MXP 1*** ***MXP 2***	***MMK 1*** ***MMK 2***	***NZD 1*** ***NZD 2***	***NGN 1*** ***NGN 2***	PKR 1 PKR 2	RUB 1 RUB 2
2021M1	**-2.56**	**2.56**	**-2.56**	**-3.74**	-2.19	**-2.79**	-0.96	**-2.98**
2021M2	**-2.56**	**2.56**	-2.35	**-3.78**	-2.02	**-2.81**	-1.06	**-2.98**
2021M3	**-2.56**	**2.56**	-2.27	**-3.82**	-2.00	**-2.80**	-1.11	**-2.93**
2021M4	**-2.56**	**2.56**	-2.17	**-3.78**	-1.94	**-2.84**	-1.02	**-2.95**
2021M5	**-2.56**	**2.56**	-2.05	**-3.74**	-1.98	**-2.83**	-1.03	**-2.88**
2021M6	**-2.56**	**2.56**	-2.14	**-3.81**	-1.93	**-2.84**	-0.80	**-2.82**
2021M7	**-2.56**	**2.56**	-2.10	**-3.85**	-1.91	**-2.91**	-0.69	**-2.68**
2021M8	**-2.56**	**2.56**	-1.99	**-3.82**	-1.90	**-2.90**	-0.79	**-2.61**
2021M9	**-2.56**	**2.56**	-1.94	**-3.80**	-1.88	**-2.84**	-0.82	**-2.60**
2021M10	**-2.56**	**2.56**	-1.92	**-3.76**	-1.90	**-2.72**	-0.84	**-2.63**
2021M11	**-2.56**	**2.56**	-1.92	**-3.55**	-1.71	**-3.94**	-0.62	**-2.75**
2021M12	**-2.56**	**2.56**	-1.50	**-3.73**	-1.68	**-3.68**	-0.71	**-2.77**
2022M1	**-2.56**	**2.56**	-1.50	**-3.79**	-1.59	**-3.64**	-0.84	**-2.71**
2022M2	**-2.56**	**2.56**	-1.53	**-3.86**	-1.67	**-3.56**	-0.95	**-2.60**
2022M3	**-2.56**	**2.56**	-1.01	**-3.87**	-1.63	**-3.46**	-0.94	-2.41
2022M4	**-2.56**	**2.56**	-1.08	-1.83	-1.64	**-3.36**	-1.34	-1.83
2022M5	**-2.56**	**2.56**	-1.01	-1.74	-1.73	**-3.57**	-1.10	-1.10
2022M6	**-2.56**	**2.56**	-1.25	-1.77	-1.65	**-3.67**	-1.29	0.32
2022M7	**-2.56**	**2.56**	-1.45	-1.81	-2.04	**-3.88**	-0.35	-0.18

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

Table 4.7. Giacomini-Rossi Fluctuation Test

Time	**LB**	**HB**	***SAR 1*** ***SAR 2***	***SGD 1*** ***SGD 2***	***ZAR 1*** ***ZAR 2***	LKR 1 LKR 2	***KRW 1*** ***KRW 2***	THB 1 THB 2
2019M4	**-2.56**	**2.56**	-2.18	**-2.82**	-2.38	-1.02	-2.54	-1.23
2019M5	**-2.56**	**2.56**	-2.19	**-2.77**	-2.35	-1.14	-2.51	-1.02
2019M6	**-2.56**	**2.56**	-2.16	**-2.72**	-2.42	-1.08	-2.52	-0.92
2019M7	**-2.56**	**2.56**	-2.15	**-2.56**	-2.47	-1.10	-2.49	-1.05
2019M8	**-2.56**	**2.56**	-2.18	**-2.57**	-2.29	-1.07	-2.51	-0.91
2019M9	**-2.56**	**2.56**	-2.11	**-2.61**	-2.27	-0.98	-2.50	-0.82
2019M10	**-2.56**	**2.56**	-2.04	**-2.65**	-2.18	-0.91	-2.50	-0.82
2019M11	**-2.56**	**2.56**	-2.06	**-2.70**	-2.12	-0.95	-2.45	-0.94
2019M12	**-2.56**	**2.56**	-2.05	**-2.71**	-2.22	-0.89	-2.44	-0.88
2020M1	**-2.56**	**2.56**	-2.02	**-2.69**	-2.06	-0.95	-2.37	-0.61
2020M2	**-2.56**	**2.56**	-2.03	**-2.62**	-2.13	-0.94	-2.22	-0.50
2020M3	**-2.56**	**2.56**	-1.88	**-2.58**	-2.28	-0.91	-2.10	-0.04
2020M4	**-2.56**	**2.56**	-2.08	-2.47	-2.23	-0.94	-2.11	0.27
2020M5	**-2.56**	**2.56**	-2.07	**-2.79**	-2.25	-1.03	-2.17	-0.26
2020M6	**-2.56**	**2.56**	-1.99	**-2.83**	-2.24	-0.55	-2.17	-0.49
2020M7	**-2.56**	**2.56**	-1.96	**-2.92**	-2.35	-0.54	-2.19	-0.47
2020M8	**-2.56**	**2.56**	-1.63	**-3.08**	-2.44	-0.43	-2.16	-0.74
2020M9	**-2.56**	**2.56**	-1.66	**-2.71**	**-2.85**	-0.44	-2.01	-0.72
2020M10	**-2.56**	**2.56**	-1.77	**-2.71**	**-2.92**	-0.43	-2.04	-0.61
2020M11	**-2.56**	**2.56**	-1.90	**-2.85**	**-2.92**	-0.47	-1.93	-0.90
2020M12	**-2.56**	**2.56**	-2.46	**-2.82**	**-2.77**	-0.58	-2.02	-0.89

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

Table 4.8. Giacomini-Rossi Fluctuation Test

Time	**LB**	**HB**	***SAR 1*** ***SAR 2***	***SGD 1*** ***SGD 2***	***ZAR 1*** ***ZAR 2***	LKR 1 LKR 2	***KRW 1*** ***KRW 2***	THB 1 THB 2
2021M1	**-2.56**	**2.56**	-2.32	**-2.74**	**-2.91**	-0.80	-1.95	-0.87
2021M2	**-2.56**	**2.56**	-2.37	**-2.57**	**-2.86**	-0.77	-2.02	-0.72
2021M3	**-2.56**	**2.56**	-2.31	**-2.62**	**-3.01**	-0.83	-2.04	-0.54
2021M4	**-2.56**	**2.56**	-2.26	**-2.61**	**-3.01**	-0.82	-2.05	-0.48
2021M5	**-2.56**	**2.56**	-2.25	-2.43	**-3.16**	-0.69	-2.08	-0.46
2021M6	**-2.56**	**2.56**	-1.97	-2.29	**-2.97**	-0.66	-2.12	-0.31
2021M7	**-2.56**	**2.56**	-2.32	-2.25	**-3.08**	-0.77	-1.92	-0.33
2021M8	**-2.56**	**2.56**	-2.49	-2.24	**-3.04**	-0.88	-1.89	-0.32
2021M9	**-2.56**	**2.56**	-2.48	-2.27	-2.45	-0.92	-1.85	-0.77
2021M10	**-2.56**	**2.56**	**-2.60**	-2.17	**-2.67**	-1.18	-1.83	-0.66
2021M11	**-2.56**	**2.56**	-2.36	**-3.27**	**-2.58**	-0.87	-2.49	-0.36
2021M12	**-2.56**	**2.56**	-2.36	**-2.99**	-2.49	-0.83	**-2.58**	-0.33
2022M1	**-2.56**	**2.56**	-2.39	**-3.09**	-2.38	-0.87	**-2.57**	-0.38
2022M2	**-2.56**	**2.56**	-2.36	**-3.34**	-2.31	-0.88	**-3.13**	-0.47
2022M3	**-2.56**	**2.56**	-2.33	**-3.47**	-1.71	0.42	**-3.17**	-0.50
2022M4	**-2.56**	**2.56**	-2.40	**-3.50**	-2.32	0.81	**-2.99**	-0.38
2022M5	**-2.56**	**2.56**	-2.39	**-3.46**	-2.32	0.74	**-3.17**	-0.37
2022M6	**-2.56**	**2.56**	-2.45	**-3.27**	-2.34	0.06	**-3.09**	-0.51
2022M7	**-2.56**	**2.56**	**-2.58**	**-3.29**	-2.37	0.04	**-3.17**	-0.77

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

Table 4.9. Giacomini-Rossi Fluctuation Test

			PHP 1	TRL 1	***GBP 1***	***AED 1***	***VND 1***	***USD 1***
Time	**LB**	**HB**	***PHP 2***	TRL 2	***GBP 2***	***AED 2***	***VND 2***	***USD 2***
2019M4	**-2.56**	**2.56**	-2.11	-2.35	**-3.10**	-2.18	-1.86	-2.18
2019M5	**-2.56**	**2.56**	-2.12	-2.28	**-3.03**	-2.19	-1.97	-2.20
2019M6	**-2.56**	**2.56**	-2.17	-2.40	**-2.97**	-2.16	-1.92	-2.17
2019M7	**-2.56**	**2.56**	-2.18	**-2.59**	**-2.62**	-2.15	-1.94	-2.16
2019M8	**-2.56**	**2.56**	-2.05	**-2.63**	**-2.90**	-2.18	-1.88	-2.18
2019M9	**-2.56**	**2.56**	-2.03	**-2.72**	**-3.09**	-2.11	-1.79	-2.11
2019M10	**-2.56**	**2.56**	-1.98	**-2.64**	**-3.18**	-2.04	-1.66	-2.05
2019M11	**-2.56**	**2.56**	-2.12	**-2.64**	**-3.24**	-2.06	-1.67	-2.06
2019M12	**-2.56**	**2.56**	-2.01	-2.52	**-3.31**	-2.05	-1.70	-2.05
2020M1	**-2.56**	**2.56**	-2.06	-2.47	**-3.34**	-2.02	-1.66	-2.02
2020M2	**-2.56**	**2.56**	-2.07	-2.48	**-3.30**	-2.03	-1.73	-2.04
2020M3	**-2.56**	**2.56**	-1.98	-2.41	**-3.26**	-1.88	-1.62	-1.88
2020M4	**-2.56**	**2.56**	-1.81	-2.37	**-3.48**	-2.08	-1.90	-2.09
2020M5	**-2.56**	**2.56**	-1.94	**-2.60**	**-3.35**	-2.07	-1.84	-2.07
2020M6	**-2.56**	**2.56**	-1.99	**-2.70**	**-3.24**	-1.99	-1.75	-2.00
2020M7	**-2.56**	**2.56**	-2.02	**-2.82**	**-3.50**	-1.96	-1.72	-1.97
2020M8	**-2.56**	**2.56**	-2.02	**-2.72**	**-3.59**	-1.63	-1.45	-1.64
2020M9	**-2.56**	**2.56**	-2.00	-2.47	**-3.48**	-1.66	-1.42	-1.67
2020M10	**-2.56**	**2.56**	-2.00	-2.24	**-3.51**	-1.77	-1.47	-1.78
2020M11	**-2.56**	**2.56**	-2.03	-2.36	**-3.40**	-1.90	-1.58	-1.90
2020M12	**-2.56**	**2.56**	-2.04	-2.32	**-3.43**	-2.45	-2.40	-2.46

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

Table 4.10. Giacomini-Rossi Fluctuation Test

Time	**LB**	**HB**	***PHP 1*** ***PHP 2***	TRL 1 TRL 2	***GBP 1*** ***GBP 2***	***AED 1*** ***AED 2***	***VND 1*** ***VND 2***	***USD 1*** ***USD 2***
2021M1	**-2.56**	**2.56**	-2.03	-2.30	**-3.19**	-2.31	-2.42	-2.32
2021M2	**-2.56**	**2.56**	-2.06	-2.12	**-3.13**	-2.37	-2.41	-2.37
2021M3	**-2.56**	**2.56**	-2.02	-2.11	**-3.21**	-2.31	-2.36	-2.31
2021M4	**-2.56**	**2.56**	-2.03	-2.08	**-3.32**	-2.26	-2.20	-2.26
2021M5	**-2.56**	**2.56**	-2.03	-2.11	**-3.39**	-2.25	-2.01	-2.25
2021M6	**-2.56**	**2.56**	-1.98	-2.10	**-3.54**	-1.97	-1.87	-1.97
2021M7	**-2.56**	**2.56**	-1.90	-2.06	**-3.49**	-2.32	-2.52	-2.31
2021M8	**-2.56**	**2.56**	-1.86	-2.06	**-3.44**	-2.49	-2.48	-2.49
2021M9	**-2.56**	**2.56**	-1.86	-1.98	**-3.36**	-2.48	-2.33	-2.48
2021M10	**-2.56**	**2.56**	-1.87	-1.71	**-3.20**	**-2.60**	-2.38	**-2.60**
2021M11	**-2.56**	**2.56**	-1.81	-0.67	**-3.55**	-2.37	-2.37	-2.36
2021M12	**-2.56**	**2.56**	-1.74	-0.63	**-3.48**	-2.36	-2.34	-2.36
2022M1	**-2.56**	**2.56**	-1.92	-0.57	**-3.47**	-2.39	-2.37	-2.39
2022M2	**-2.56**	**2.56**	-1.98	-0.56	**-3.17**	-2.36	-2.34	-2.36
2022M3	**-2.56**	**2.56**	-2.17	-0.40	**-3.22**	-2.34	-2.47	-2.33
2022M4	**-2.56**	**2.56**	-1.90	-0.44	**-3.32**	-2.41	-1.86	-2.40
2022M5	**-2.56**	**2.56**	-2.31	-0.67	**-3.32**	-2.40	-2.13	-2.39
2022M6	**-2.56**	**2.56**	**-2.61**	-0.68	**-3.25**	-2.45	-2.49	-2.45
2022M7	**-2.56**	**2.56**	**-2.66**	-0.59	**-3.04**	**-2.59**	**-2.63**	**-2.58**

Footnote: "LB" and "HB" represent the critical values of the lower-bound and upper-bound for the fluctuation test of Giacomini and Rossi (2010). The exchange rate forecasts generated from the large VAR and random-walk models are respectively labelled as "Exchange Rate Code + 1" and "Exchange Rate Code + 2".

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