Forecasting Daily Exchange Rates with Stock Return Differential

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Abstract

Inspired by uncovered equity parity (UEP), this study uses daily data to show that stock return differential has strong in-sample and out-of-sample predictive power in nominal exchange rates at short horizons (1-day-ahead predictions).

Keywords : exchange rates, forecasting, stock return differenetial

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1 Introduction

Beating the random walk in forecasting nominal exchange rates in out-of-sample predictions is one of the major challenges in international economics. In practice, Meese and Rogoff (1983) document exchange rate forecasting with macroeconomic fundamentals at short horizons has been frustratingly disappointing. Cheung et al. (2005) also show that no single exchange rate model can consistently outforecast random walk model in out-of-sample predictions considering a variety of forecasting horizons.

Although Molodtsova and Papell (2009) provide strong evidence of short-horizon exchange rate predictability with Taylor rule fundamentals base on the out-of sample test statistic developed by Clark and West (2007). Rogoff and Stavrakeva (2008) argues that test suggested by Clark and West (2007) is more likely to test whether exchange rate follows a random walk rather than the proposed model outperforms the random walk model. That is, the out-of-sample forecasting performance is overpraised built on "misinterpretation of some newer out-of-sample test statistics for nested models".

Furthermore, the traditional exchange rate forecasting literature tend to use macroeconomic fundamental as the predictor (e.g., Mark (1995), Mark and Sul (2001) and Engel et al. (2007)). However, the fundamental exchange rate model is not feasible for a real-time forecasting experiment. There is a time lag between the reference period and the announcement release time and often subject to large revisions in the macroeconomic fundamental variables such as price level, real output and money supply.

The objective of this study is to propose a new predictor of exchange rate movements which can be used in real-time data forecasts, namely the stock return differential between domestic stock and the U.S. stock. The stock prices are readily available and not subject to revision, which is desirable for real-time forecasters. The theoretical relationship between exchange rates and stock returns has been well documented in Hau and Rey (2006), a new theory is proposed which known as the Uncovered Equity Parity (UEP). According to UEP, consider a domestic investor with money invested both in domestic and foreign equity market. When foreign equity market relatively outperforms domestic market, domestic investors are overweight of foreign equities and exposed to higher exchange rate exposure. To return to a neutral position, sells some foreign equities and foreign currency and buy some domestic currency to reduce exchange rate risk. The sale of foreign currency for domestic currency leads foreign currency depreciate at the same time that foreign market is outperforming. The UEP suggests that a strong equity market is associated with a weak currency because of portfolio rebalancing.

The statistical validity of UEP condition has been verified in Lustig et al. (2011), Menkhoff et al. (2012), Melvin and Prins (2015) and among others. Nevertheless, Cenedese et al. (2016) finds that the explanatory power of stock returns for exchange rate movements is limited with monthly data. To evaluate the empirical evidence of the UEP, it is particularly useful to use high-frequency data. The portfolio rebalancing behavior is commonly used in high-frequency trading to hedge its investment position. The predictive power of stock return differential would be insignificant if lower-frequency data is used (namely, monthly or quarterly) under the mechanism that UEP suggested. It would likely appear as contemporaneous relationships instead of lead–lag dynamics in predictive regression model. Moreover, as pointed by Ferraro et al. (2015), the exchange rate predictive ability may be much stronger in daily data.

In this study, we use daily data to show that the stock return differential has strong in-sample and out-of-sample predictive power in nominal exchange rates. The in-sample tests are based on the significance of coefficient (t-test) from a 1-day-ahead predictive regression model. The mean squared prediction error (MSPE) is used to evaluate out-of-sample forecast performance. We find that stock return differential is outperforms random walk model in 5 of 6 currency pairs (EUR/USD, JPY/USD, GBP/USD, AUD/USD, and CAD/USD).[1] Moreover, the results are robust with respect to a alternative benchmark model (historical mean model), a alternative forecasting objective (the level of exchange rates), and other

[1] We use direct quotation for all currencies pairs for consistency.

currency pairs (HKD/USD, KRW/USD and NTD/USD).

The structure of the paper is organized as follows. Section 2 presents the theoretical motivation of the proposed predictor. Section 3 describes the empirical framework. Data descriptions are reported in section 4 and section 5 provides the empirical results. Section 6 explores the robustness of the empirical findings and conclusions follow in section 7.

2 Theoretical Motivation of the Proposed Predictors

In this section, we introduce briefly the basic relationship between stock return differential and exchange rate movements that the uncovered equity parity (UEP) suggested. For more details, please refer to Hau and Rey (2006) and Cochrane (2009). To prevent arbitrage opportunities, the following Euler equation must be satisfied:

$$E_t\left(R^i_{t+1}m^j_{t+1}\right) = 1, \text{ for } i \text{ and } j \in \{d, f\}, \tag{1}$$

where R_{t+1} is the gross return on equity market, m_{t+1} is the stochastic discount factor of investor, d and f respectively stands for domestic and foreign.

Equation (1) must hold for all investors and all equity markets. Assume that a domestic investor formulates a portfolio that consists domestic and foreign stocks. Let S_t be the nominal bilateral exchange rate (direct quote), then from domestic investor's the perspective, the return of the foreign investment is $R^d_{t+1}\frac{S_{t+1}}{S_t}$. In the absence of arbitrage opportunities, then equation (1) can be rewritten as follows:

$$E_t\left(R^f_{t+1}\frac{S_{t+1}}{S_t}m^d_{t+1}\right) = E_t\left(R^d_{t+1}m^d_{t+1}\right). \tag{2}$$

Under risk neutrality, equation (2) implies that the UEP condition holds in the following form:

$$E_t\left(R^f_{t+1}\frac{S_{t+1}}{S_t} - R^d_{t+1}\right) = 0. \tag{3}$$

If domestic investor expect the domestic stock market relatively outperforms foreign stock market, then any differences in equity returns will be eliminated by exchange rate movements. That is, UEP argues that $E_t(R^d_{t+1}) > E_t(R^f_{t+1})$ implies $E_t(S_{t+1}) > S_t$, a strong domestic stock market causes the domestic currency to depreciate.

The correlation of stock return differential and exchange rate movements predicted by UEP contradict to the "conventional wisdom" that a strong equity market comes with a strong currency. However, the existing literature also suggests that the correlation may take the opposite sign. For example, considering the risk premium (see Cenedese et al. (2016)) or the behavior of trend chasing or momentum investing (e.g., Bohn and Tesar (1996) and Griffin et al. (2004)). In this study, we do not expect the correlation of stock return differential and exchange rate movements should be negative or positive. Instead, we focus on the predictive power of stock return differential in currency movements.

3 Econometric Framework

3.1 In-Sample Predictive Regression Models

This paper studies daily nominal-exchange-rate movements predictability based on stock return differentials. The goal of this paper is to provide a potential trading strategy with respect to exchange rate movements. We first consider the following 1-day-ahead predictive regression model for in-sample tests:

$$s_{t+1} - s_t = \alpha + \beta x_t + u_{t+1}, \tag{4}$$

where s_t is the (log) nominal exchange rate, is the number of domestic currency per unit of U.S. dollars. An increase in s_t means a depreciation of domestic currency against U.S. dollars. The predictor variable is the stock return differential ($x_t = \Delta sp_t - \Delta sp^*_t$), where sp_t is the (log) stock price index) and asterisk denotes variables in the foreign country (the U.S.). We test the null hypothesis of no predictive power for future exchange rate movements $\beta = 0$ against $\beta \neq 0$. We use Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors to construct the t–statistic.

3.2 Out-of-Sample Forecasts

The total sample T is divided into two parts (in- and out-of-sample portions). There are R in-sample observations, $t = 1, \ldots, R$, and P out-of-sample observations, $t = R+1, \ldots, R+P$. Obviously, $R + P = T$. The predictive regression model is

$$s_{t+h} - s_t = \alpha + \beta x_t + u_{t+h}, \tag{5}$$

The forecast horizon h is 1, 2, 3, 5, and 20 days. When $h = 5$ and $h = 20$ is correspond to forecast weekly and monthly changes of exchange rates. The h-step-ahead pseudo out-of-sample forecast of the daily exchange rate is obtained by:

$$\widehat{s}_{t+h} = s_t + \widehat{\alpha}_t^h + \widehat{\beta}_t^h x_t, t = R, R+1, \ldots, T-h, \tag{6}$$

where $\widehat{\alpha}_t^h$ and $\widehat{\beta}_t^h$ are estimated by the rolling scheme with a fixed window width.

In consideration of parameter instability in exchange rate forecasting (for instance, Wolff (1987)), we use rolling approach instead of recursive method. However, the empirical result depends on the choice of the rolling window R. A large R reduces the forecast variance but increases the bias of parameter due to distant information and a small R decreases the bias but the forecast variance increases. If the researcher considers a variety of rolling windows and report the empirical result based on the "best" rolling window (the rolling windows that generates best empirical result, i.e., smallest mean square prediction errors (MSPE)), then the tests based on the chosen rolling window do not have correct size (see Pesaran and Timmermann (2007), Rossi and Inoue (2012) and Inoue et al. (2017) for details). To investigate whether the empirical evidence depend on choices of window sizes, we report the empirical results based on all feasible rolling windows. The maximum window size is $0.85T$, the minimum window size is 1000 and the increment is 100.

For a given rolling window width R, $\widehat{\alpha}_t^h$ and $\widehat{\beta}_t^h$ are calculated by

$$\widehat{\beta}_t^h = \frac{\sum_{i=t-R+h+1}^{t}(x_{i-h} - \bar{x}_{t-h})(y_i^h - \bar{y}_t^h)}{\sum_{i=t-R+h+1}^{t}\left(x_{i-h} - \bar{x}_{t-h}\right)^2}, \tag{7}$$

$$\widehat{\alpha}_t^h = \bar{y}_t - \widehat{\beta}_t \bar{x}_{t-h}, \tag{8}$$

$$\bar{x}_{t-h} = \frac{\sum_{i=t-R+1}^{t-h} x_i}{R-h}, \tag{9}$$

$$\bar{y}_t^h = \frac{\sum_{i=t-R+h+1}^{t} y_i^h}{R-h}, \tag{10}$$

where $y_t^h = s_t - s_{t-h}$.

To evaluate the out-of-sample forecasting accuacy, we use MSPE as a measure of prediction performance. The benchmark is the driftless random walk model. Letting $\mathcal{M}^{\mathcal{RW}}$ and $\mathcal{M}^{\mathcal{SRD}}$ denote the random walk model and the predictive regression model based on the stock return differential, respectively. Thus the h-step-ahead squared prediction errors of the two models at time $t+h$ are:

$$e_{t+h}^2(\mathcal{M}^{\mathcal{RW}}) = (s_{t+h} - s_t)^2 \tag{11}$$

$$e_{t+h}^2(\mathcal{M}^{\mathcal{SRD}}) = \left(s_{t+h} - s_t - \left(\widehat{\alpha}_t^h + \widehat{\beta}_t^h x_t\right)\right)^2 \tag{12}$$

Clearly, if $\widehat{\alpha}_t^h + \widehat{\beta}_t^h x_t$ and $s_{t+h} - s_t$ have the same sign (both positive or both negative), thus the stock return differential has a lower squared prediction error than the random walk model at time $t+h$.

Let $MSPE(\mathcal{M}^{\mathcal{RW}})$ and $MSPE(\mathcal{M}^{\mathcal{SRD}})$ respectively denotes the average of Equation (11) and (12) for the out-of-sample period. To access whether $MSPE(\mathcal{M}^{\mathcal{SRD}})$ is significantly less than $MSPE(\mathcal{M}^{\mathcal{RW}})$, the Diebold and Mariano (1995) and the Clark and West (2007) MSPE-adjusted test statistic is used to test the following null hypothesis against the alternative hypothesis that the suggested model is more accurate than the driftless random walk model:

$$H_0 : MSPE(\mathcal{M}^{\mathcal{SRD}}) = MSPE(\mathcal{M}^{\mathcal{RW}})$$

$$H_1 : MSPE(\mathcal{M}^{\mathcal{SRD}}) < MSPE(\mathcal{M}^{\mathcal{RW}}).$$

Although we have a larger sample size by using daily data, the critical values are obtained from a bootstrap approach based on 1000 iterations. Notice that it gives more weight to large errors when calculating MSPE. If $MSPE(\mathcal{M}^{\mathcal{SRD}})$ is significantly less than $MSPE(\mathcal{M}^{\mathcal{RW}})$, it does not imply stock return differential is able to predict the sign of currency movements more correctly than the random walk model (or a 50/50 coin toss), but it does imply stock return differential can predict large swings in exchange rates, which is attractive for a trading strategy.

4 Data Descriptions

To evaluate the empirical evidence of equation (4) and (5), it is particularly useful to use daily data. The portfolio rebalancing behavior (or trend-chasing) is commonly used in high-frequency trading to hedge its investment position. The predictive power of stock return differential would be insignificant if lower-frequency data is used (namely, monthly or quarterly) under the mechanism that UEP suggested. It would likely appear as contemporaneous relationships instead of lead-lag dynamics as described in Equation (4).

The 7 most-traded currencies in 2016 are US dollar (USD), Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Australian Dollar (AUD), Swiss Franc (CHF) and Canadian dollar (CAD). Thus we evaluate the exchange rate forecasting performance of EUR/USD, JPY/USD, GBP/USD, AUD/USD, CHF/USD and CAD/USD.

The nominal exchange rates data are obtained from FRED, and stock prices are collected from Yahoo Finance. The sample periods all end on 31 March 2017 but the starting points vary by currency due to equity data availability of Yahoo Finance. Table (1) describes the data sources and codes reviewed. The European Union, the United Kingdom and Australia use indirect quotation. For the purposes of consistency, we convert indirect quotation into direct quotation. Stock returns are measured by changes in the (log) representative stock price index in each country. Figure (1) plots the daily data of the nominal exchange rate, and the representative stock price indices are plotted in Figure (2).

5 Empirical Results

5.1 In-Sample Predictive Regression Results

In-sample predictive regression results based on the estimation of Equation (4) are reported in Table (2). The Bartlett kernel is used to construct the Newey–West HAC standard errors, where the truncation parameter is determined by rounding $0.75T^{1/3}$ to the nearest integer. Figures (3) plots scatter diagrams and fitted regression lines.

Excepting CHF/USD, the estimates of β for the other 5 currency pairs are statistically significant at the 0.05 level. The estimation result of JPY/USD detects evidence of trend-chasing behavior by investors, trend-chasing by investors leads domestic currency to appreciate on the next trading day when domestic stock market outperformed foreign (the U.S.) market. The sign of the estimated coefficients in EUR/USD, GBP/USD, AUD/USD and CAD/USD are consistent with UEP, a positive stock return differential is accompanied by a depreciation of domestic currency . In summary, our in-sample analysis suggest that stock return differential has in-sample explanatory power for currency movements.

5.2 Out-of-Sample Forecasting Performance

Due to parameter instability, it is widely known that models that fit well in-sample are not guaranteed to good out-of-sample forecasting performance. In fact, future exchange rates have been shown to be extremely difficult to forecast. It would be exciting if we find that stock return differential has predictive power for currency movements. Notice that even for the smallest sample (EUR/USD, $T = 4267$) with the largest rolling window size (0.85T), the out-of-sample period still contains more than 600 observations. In addition, it includes more than 8400 observations for the largest sample (CAD/USD, $T = 9410$) with the smallest window size (1000). More observations in out-of-sample period is more likely to cover those periods when exchange rate movements are volatile or smooth, thus the statistical inference would be more convincing.

We now move focus to out-of-sample tests to evaluate exchange rate predictability. Figure (4) to (8) plot the MSPE ratio ($MSPE(\mathcal{M}^{\mathcal{SRD}})/MSPE(\mathcal{M}^{\mathcal{RW}})$) with respect to different rolling window sizes at horizons of 1,2,3,5 and 20. The corresponding bootstrap p-values of the test suggested by Diebold and Mariano (1995) and the Clark and West (2007) are plotted in Figure (9) to (13). The Diebold-Mariano test is a minimum mean square forecast error test, one rejects the null hypothesis may conclude the proposed model gives better out-of-sample forecasting performance. Clark and West (2006) document that the Diebold-Mariano test is poorly sized, thus the adjusted mean square prediction error (MSPE-Adj) test proposed by Clark and West (2007) yielded more accurately sized. But Rogoff and Stavrakeva (2008) point that the implication of the MSPE-Adj test is to test whether the independent variable follows the random walk or not. In other words, a significant MSPE-Adj test statistic does not always imply the proposed model outperforms the random walk model. Therefore, we report both test statistics to check the robustness of the empirical results.

The 1-day-ahead forecasting results shows that the forecasts for exchange rate movements based on stock return differential significantly produce lower MSPEs than the random walk model at the 5% level with respect to most of rolling window sizes in AUD/USD, CAD/USD, GBP/USD and JPY/USD. Stock return differential may reduces the MSPEs at most by between 0.2% (for CHF/USD) to 3.7% (for AUD/USD). The reductions seems small is because daily exchange rate movements is quite noisy. For those currencies which the estimated coefficient $\widehat{\beta}$ is positive and significant, the predictive power are particularly strong. The predictive ability is significant only for small rolling window sizes in EUR/USD, this fact suggests that the parameter value of β may vary over time. For CHF/USD, the bootstrap p-values of Diebold and Mariano (1995) is never less than 0.3. The out-of-sample results are consistent with in-sample analysis.

Suppose the predictive power of stock return differential on exchange rates is base on the portfolio rebalancing (or trend-chasing) behavior, then the predictive ability should be appeared at short horizons because the behavior is associated with High-frequency trading.

The result is similar but less significant at $h = 2$. As expected, the predictive power is limited for those horizons greater than 3. The out-of-sample forecasting results can be summarized into a strong evidence that the stock return differential may help to predict the nominal exchange rate out-of-sample at 1-day-ahead forecasts, and the results are robust with respect to different window sizes.

6 Robustness Checks

To check the robustness of the out-of-sample forecasting results, we consider the following three modifications. To start with, we consider different benchmark models as comparisons of forecasting performance. In addition, instead of forecasting the percentage changes in the exchange rate, we evaluate the out-of-sample predictability in terms of the level of exchange rates directly. Finally, we explore the external validity by extending our analysis to other countries in Asia. In the following robustness checks, we will focus only on 1-day-ahead forecasts.

6.1 Alternative Benchmark Model

The random walk model is used as the benchmark for the out-of-sample forecasting performance. Suppose there is a short-run trend in the daily exchange rates, thus the random walk model will underperform because it does not capture the short-run trend. Following Campbell and Thompson (2008), we now consider a historical average model as an alternative benchmark.

For a given rolling window size R, the 1-day-ahead historical average forecast at time t is obtained by

$$\widehat{s}_{t+1} = s_t + \overline{\Delta s_t}, \tag{13}$$

where $\overline{\Delta s_t}$ is the sample average of $s_t - s_{t-1}$ of last R observations. Obviously, using a historical average model as a benchmark can be interpreted as we investigate where the forecasting power is come from. If the stock return differential model is only able to beat the random walk but not the historical average model, it suggests that the predictivity is based on the short-run trend rather than the stock return differential. Otherwise, the predictive power of stock return differential is then confirmed if the model beats both the random walk and the historical average model.

The corresponding empirical results plotted in Figure (14) and (15) are quantitatively and qualitatively similar to the previous results. The results show that short-run trend plays a less significant role in exchange rate movements and provide strong evidence the exchange rate predictability using stock return differential.

6.2 Forecast the Level of Exchange Rate

Although it is common to forecast the changes in log exchange rate in the exchange rate forecasting literature. As pointed by Baumeister and Kilian (2012), investors care about the level of exchange rates rather than the log exchange rates. We now replace our objective by forecast the level of exchange rates.

The predictive model is:

$$\frac{S_{t+1} - S_t}{S_t} = \alpha + \beta x_t + u_{t+h}, \tag{14}$$

where S_t is the nominal exchange rate. The 1-step-ahead forecast of the level of exchange rate is obtained by:

$$\frac{\widehat{S_{t+1}} - S_t}{S_t} = \widetilde{\alpha}_t + \widetilde{\beta}_t x_t \, , t = R, R+1, \ldots, T-1, \tag{15}$$

where $\widetilde{\alpha}_t$ and $\widetilde{\beta}_t$ are estimated by a rolling scheme. Hence, the forecast of the level of exchange rate is then constructed by :

$$\widehat{S_{t+1}} = S_t \times \left(1 + \widetilde{\alpha}_t + \widetilde{\beta}_t x_t\right). \tag{16}$$

Figure (16) and (17) plot the results. The evidence is even stronger when we forecasting the level of exchange rate directly.

6.3 External Validity

In this subsection, we extend our analysis to Hong Kong (HKD/USD), South Korea (KRW/USD), Singapore (SGD/USD) and Taiwan (NTD/USD), as known as the Four Asian Tigers. These countries have developed equity markets. The data source is described in Table (3), the original time series are plotted in Figure (18) and (19). As can be seen, the movements in HKD/USD are quite small due to its fixed-exchange-rate policy, which is more favorable for the random walk model. However, little fluctuation in exchange rate is still observable.

The in-sample results are reported in Table (4), the out-of-sample results are plotted in Figure (21) and (22). The estimated coefficients are all positive but insignificant in HKD/USD and SGD/USD. The out-of-sample results suggests that stock return differential predicts KRW/USD movements if small window size is used, it reduces the MSPE up to 4%. The HKD/USD movements is predictable if large window size is used. For NTD/USD, the predictive ability is ephemeral with respect to some of the particular window sizes. The result of SGD/USD is similar to CHF/USD, it is almost unpredictable.

To sum up, consistent with previous result, stock return differential does not predict exchange rate movements in all currencies. But for most currencies, it has predictive power on the 1-day-ahead exchange rate.

7 Conclusions

Economists usually have no much luck in exchange rate forecasting. In this study, we perform in-sample and out-of-sample exercises to assess exchange-rate forecastability. We shed light on forecasting exchange rates using stock return differential. This paper uncovers the interactions between stock and foreign exchange markets, we find that the domestic currency will depreciate on the next trading day when domestic stock market outperformed foreign (the U.S.) market, which suggest that the UEP condition holds. Using a rich set of daily data, we find that stock return differential has strong in-sample and out-of-sample predictive ability in 5 of the 6 most-traded currencies (and 3 of 4 Asian currencies in the robustness check). Our empirical evidence implies that daily exchange rate are not random walks. Furthermore, it is predictable.

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Table 1: Data Sources

Variable Name	Source	Code
The U.S.		
S&P 500 Index	Yahoo Finance	GSPC
European Union: From 2000-1-3 to 2017-3-31 (T = 4267)		
Nominal Exchange Rates	FRED	DEXUSEU
Euronext 100 Index	Yahoo Finance	N100
Japan: From 1984-1-5 to 2017-3-31 (T = 7882)		
Nominal Exchange Rates	FRED	DEXJPUS
Nikkei 225 index	Yahoo Finance	N225
The U.K.: From 1984-1-4 to 2017-3-31 (T = 8206)		
Nominal Exchange Rates	FRED	DEXUSUK
FTSE 100 index	Yahoo Finance	FTSE
Switzerland: From 1990-11-13 to 2017-3-31 (T = 6455)		
Nominal Exchange Rates	FRED	DEXSZUS
Swiss Market Index	Yahoo Finance	SSMI
Australia: From 1992-11-24 to 2017-3-31 (T = 5965)		
Nominal Exchange Rates	FRED	DEXUSAL
S&P/ASX 200 index	Yahoo Finance	AXJO
Canada: From 1979-7-2 to 2017-3-31 (T = 9410)		
Nominal Exchange Rates	FRED	DEXCAUS
S&P TSX Composite index	Yahoo Finance	GSPTSE

Table 2: In-Sample Predictability

	$\widehat{\beta}$	Std. Error	t-stat	$Pr(>\|t\|)$
Australia	0.0839	0.0198	4.23	0.00
Canada	0.0400	0.0112	3.56	0.00
Switzerland	-0.0092	0.0106	-0.87	0.38
European Union	0.0402	0.0136	2.97	0.00
The United Kingdom	0.0218	0.0106	2.06	0.04
Japan	-0.0175	0.0057	-3.09	0.00

Notes: The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + u_{t+1}$. We test the null hypothesis that $\beta = 0$ against $\beta \neq 0$. Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard errors are used to construct the t−statistic.

Table 3: Robustness Check: Other Countries, Data Sources

Variable Name	Source	Code
Hong Kong: From 1987-1-2 to 2017-3-31 ($T = 7277$)		
Nominal Exchange Rates	FRED	DEXUKUS
Hang Seng Index	Yahoo Finance	HSI
South Korea: From 1997-7-2 to 2017-3-31 ($T = 4690$)		
Nominal Exchange Rates	FRED	DEXKOUS
KOSPI Composite Index	Yahoo Finance	KS11
Singapore: From 1987-12-29 to 2017-3-31 ($T = 7106$)		
Nominal Exchange Rates	FRED	DEXSIUS
Singapore Stock Market Index	Yahoo Finance	STI
Taiwan: From 1997-7-3 to 2017-3-31 ($T = 4673$)		
Nominal Exchange Rates	FRED	DEXTAUS
TSEC weighted index	Yahoo Finance	TWII

Table 4: Robustness Check: In-Sample Predictability

	$\widehat{\beta}$	Std. Error	t-stat	$Pr(>\|t\|)$
Hong Kong	0.0004	0.0003	1.53	0.13
South Korea	0.0443	0.0164	2.70	0.01
Singapore	0.0010	0.0040	0.25	0.81
Taiwan	0.0088	0.0031	2.84	0.00

Note: See notes to Table (2).

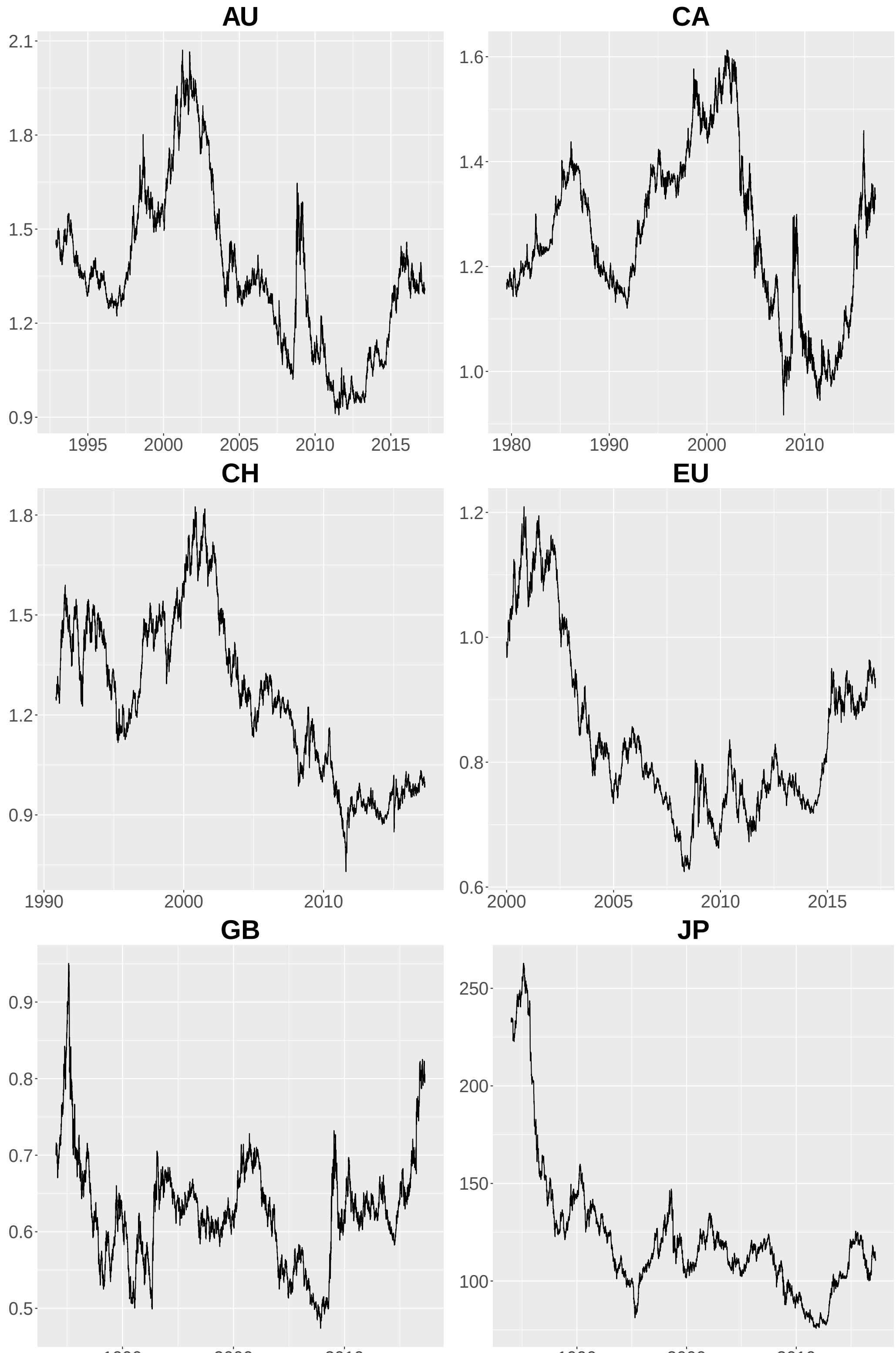


Figure 1: Nominal Exchange Rates

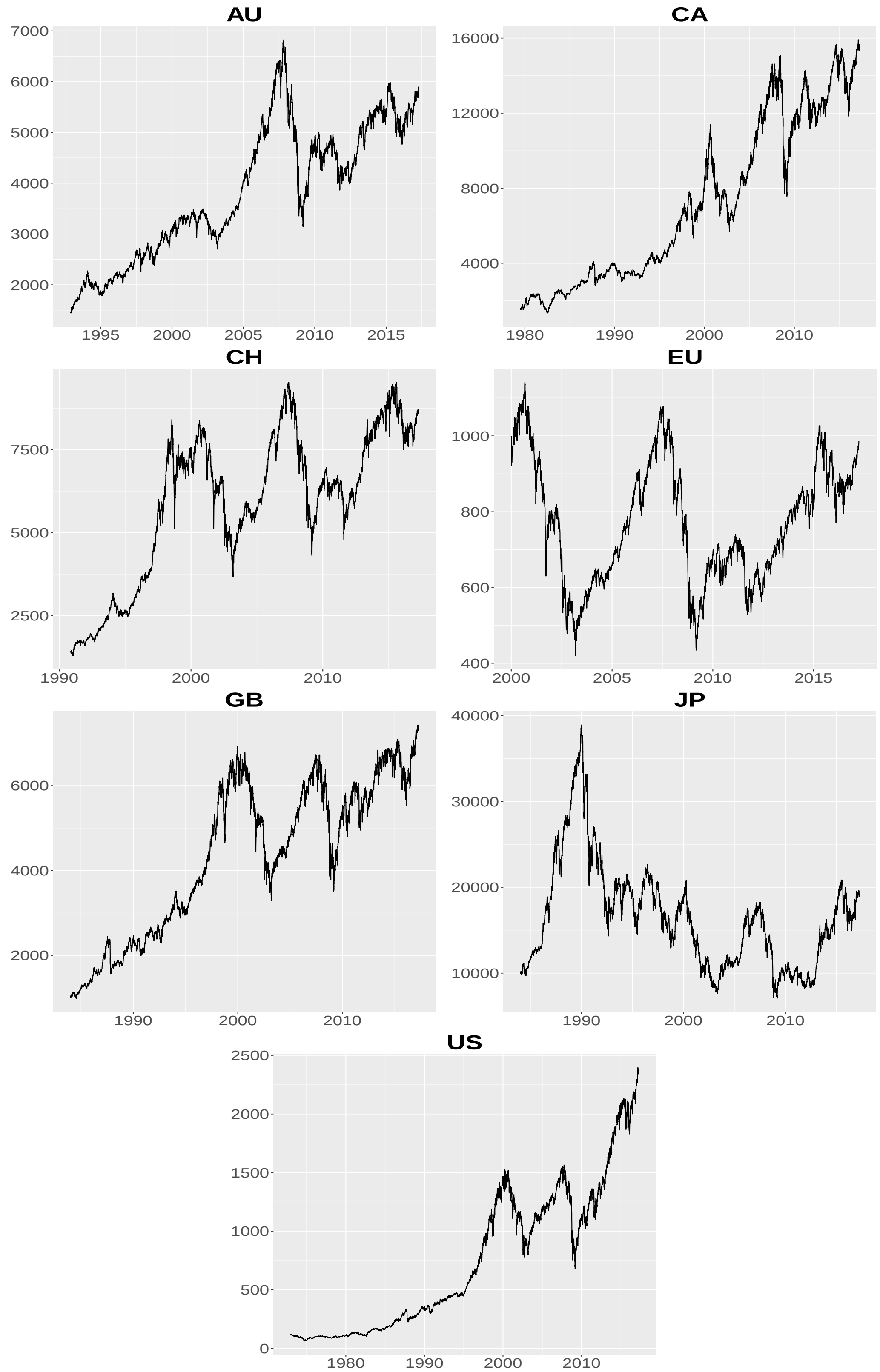


Figure 2: Stock Price Indices

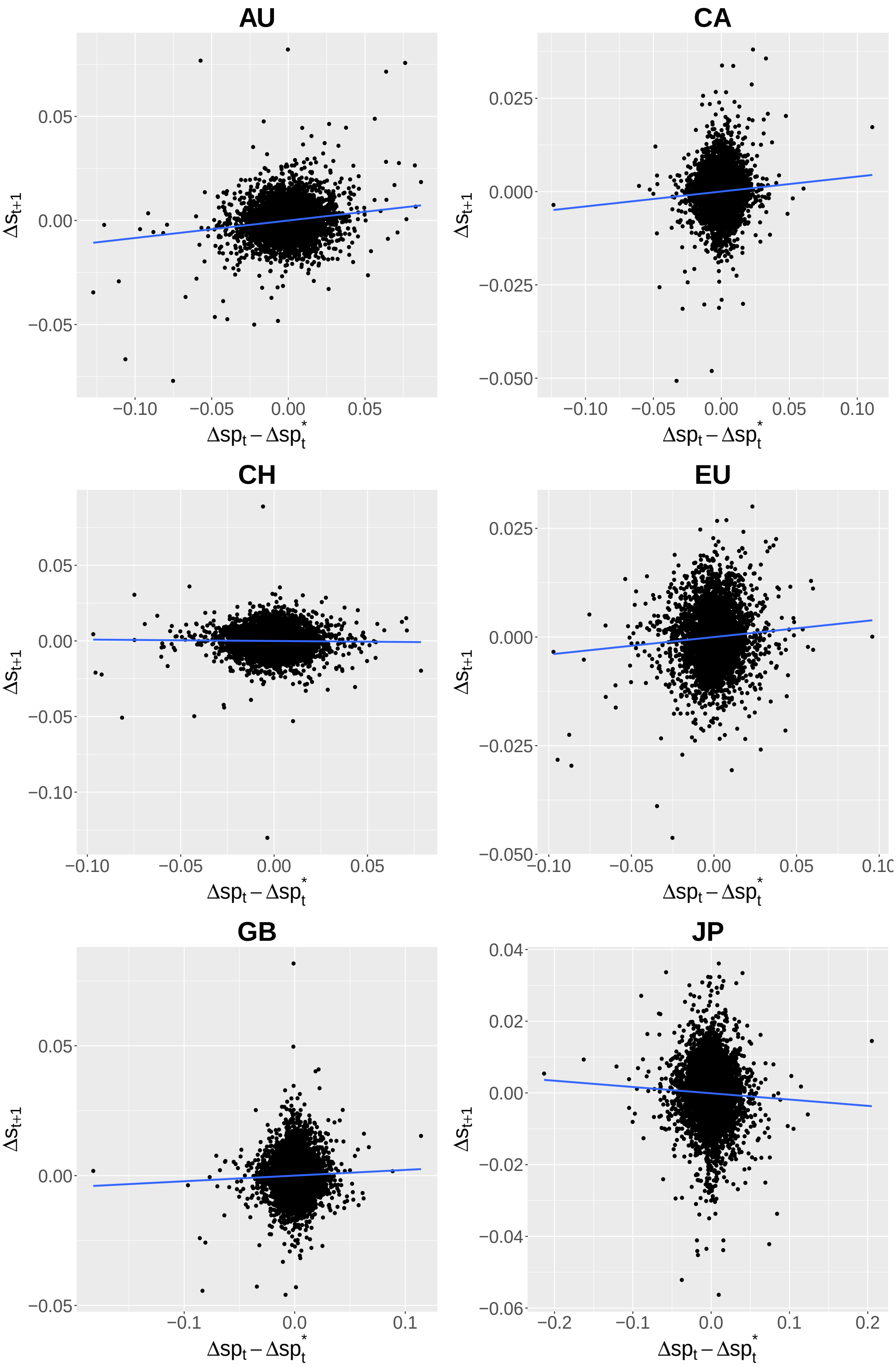


Figure 3: Scatter Diagram of $\Delta sp_t - \Delta sp_t^*$ versus Δs_{t+1}

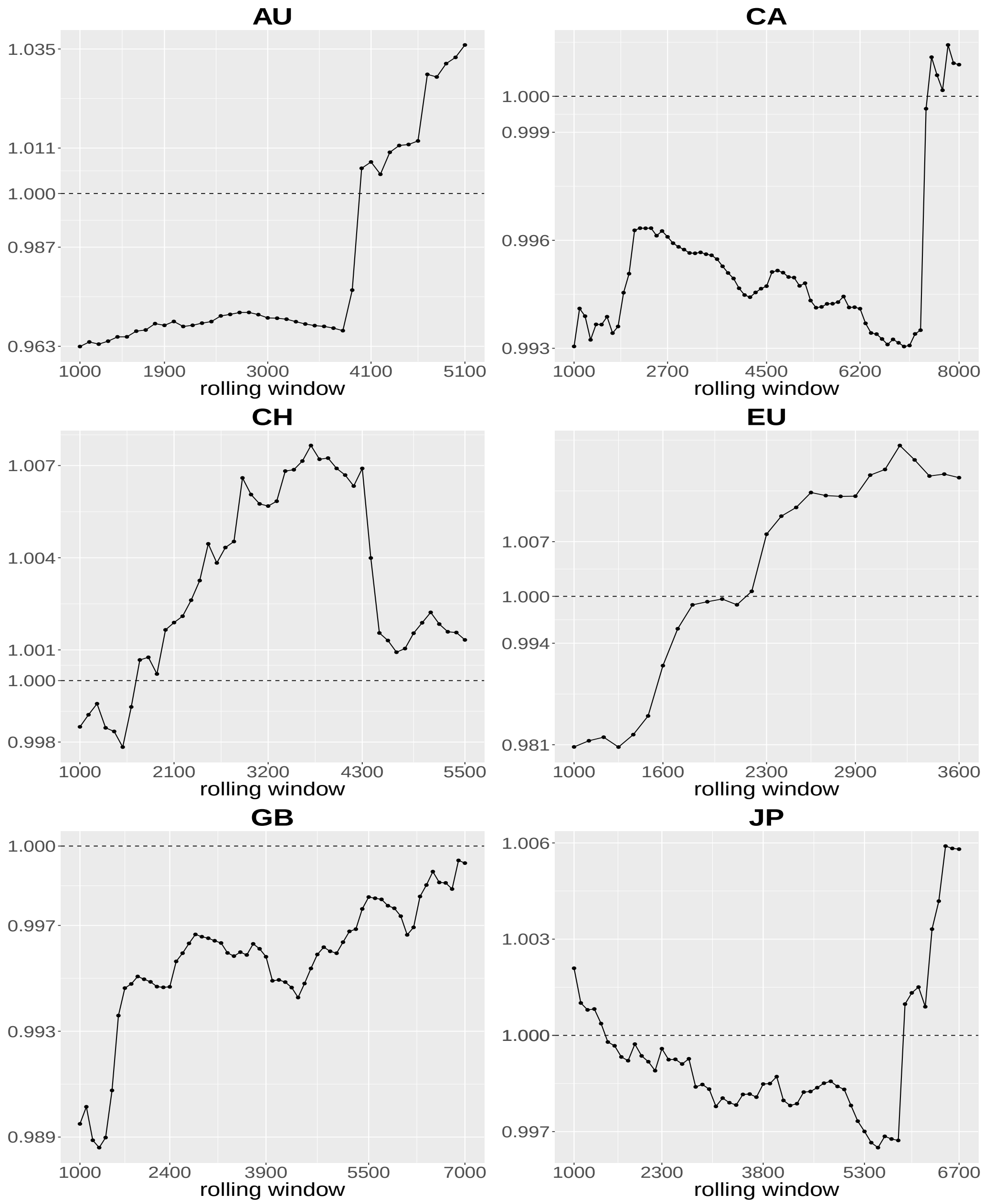


Figure 4: The Rolling Window Width and its Corresponding MSPE Ratios ($h = 1$)

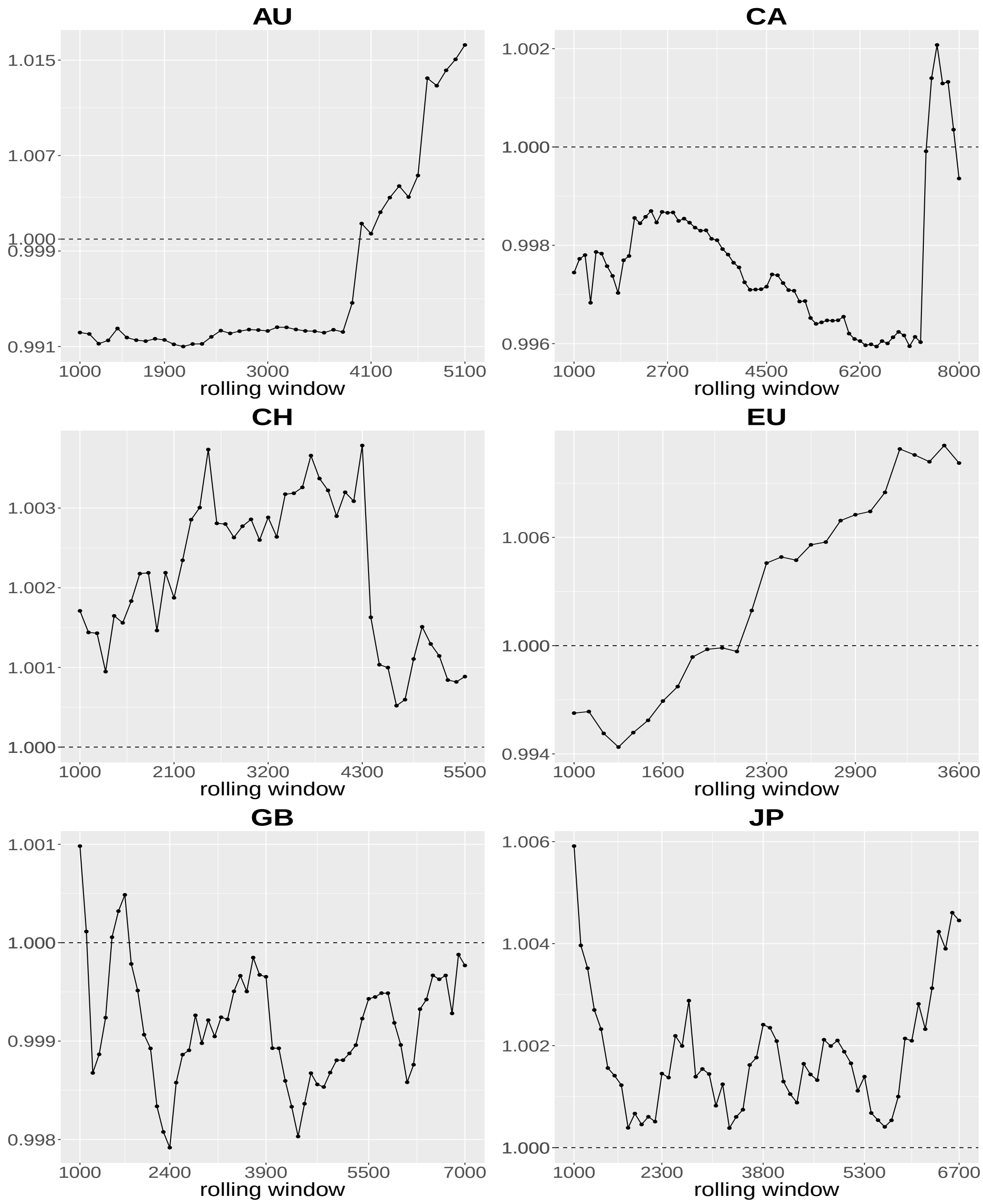


Figure 5: The Rolling Window Width and its Corresponding MSPE Ratios (h = 2)

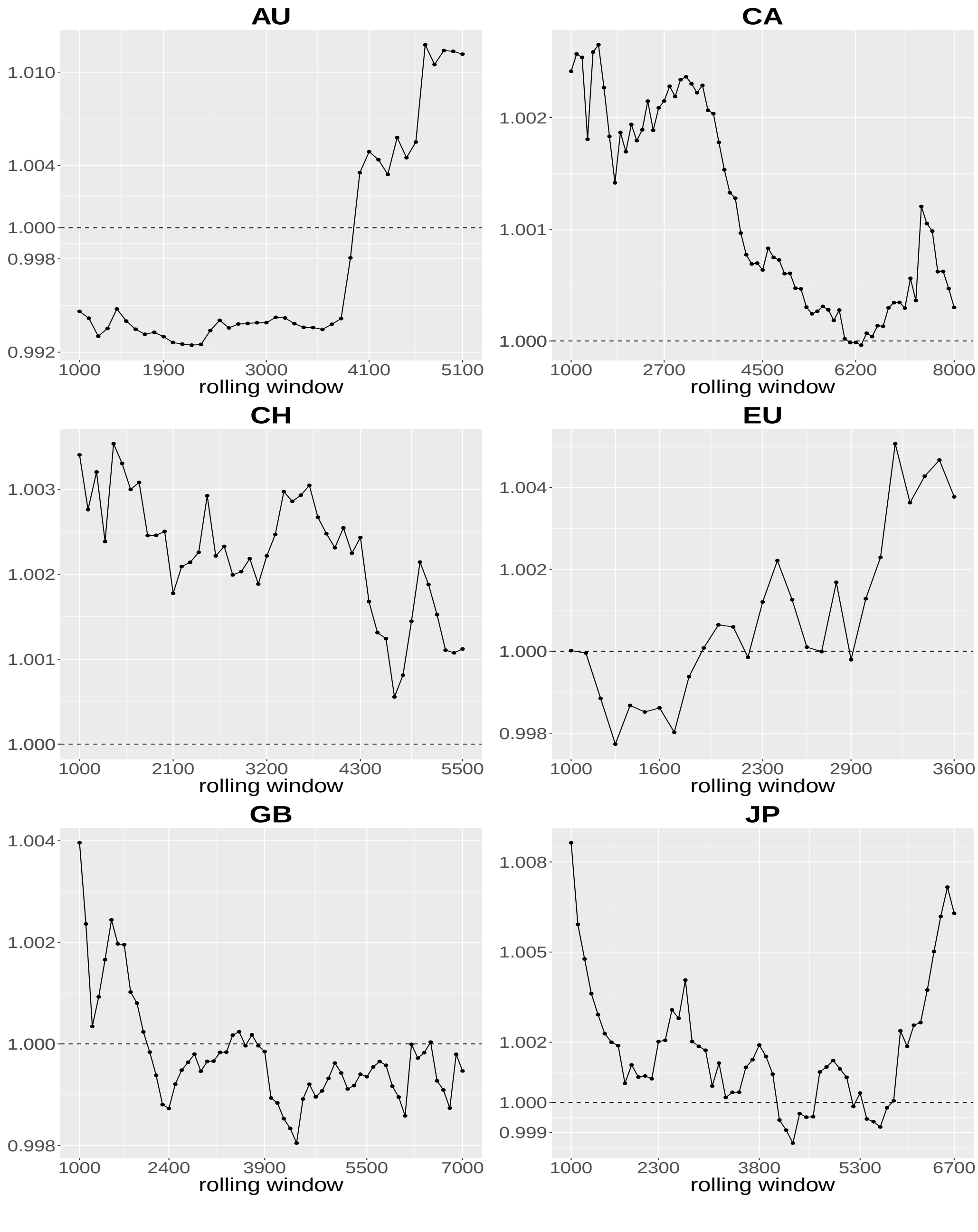


Figure 6: The Rolling Window Width and its Corresponding MSPE Ratios (h = 3)

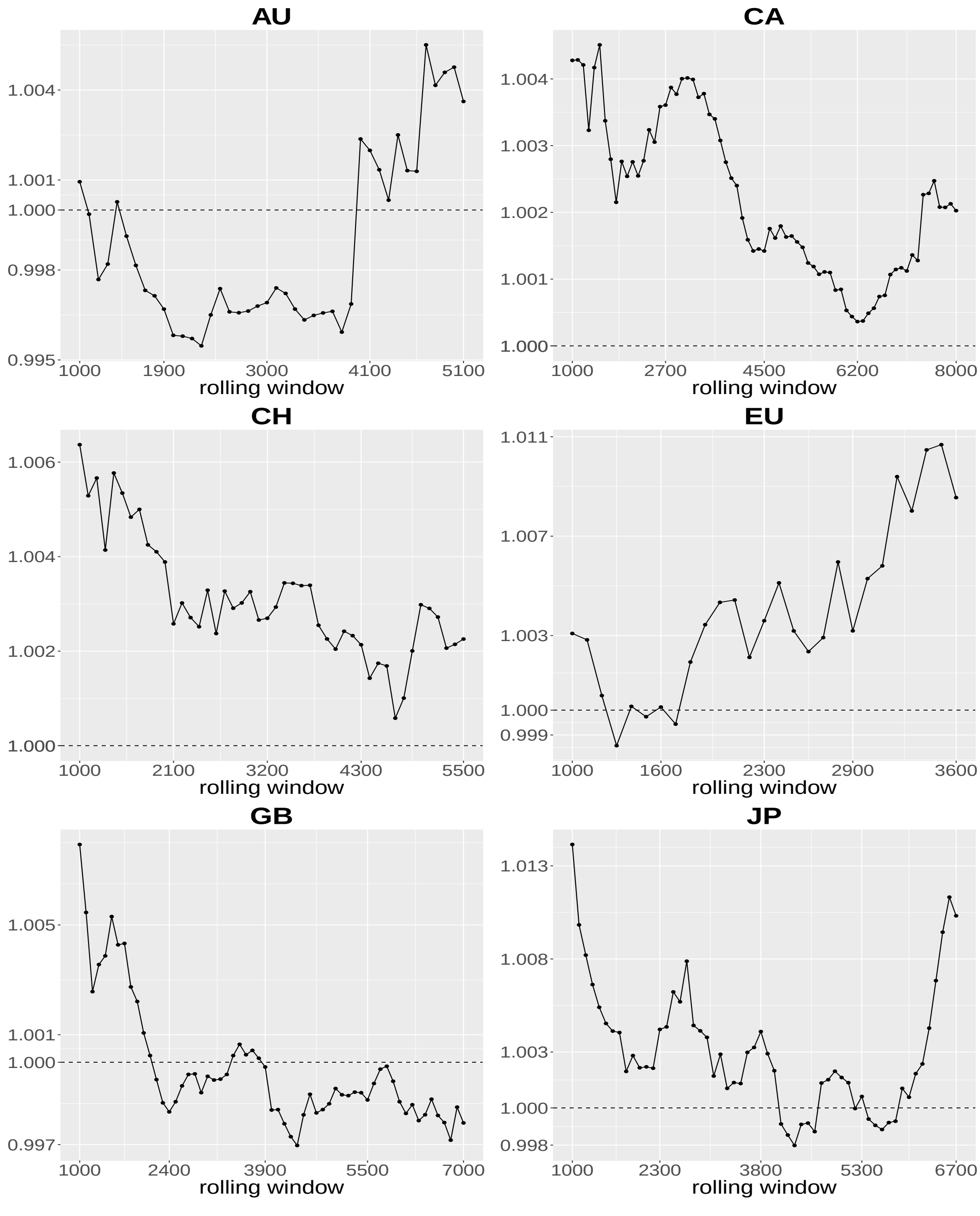


Figure 7: The Rolling Window Width and its Corresponding MSPE Ratios ($h = 5$)

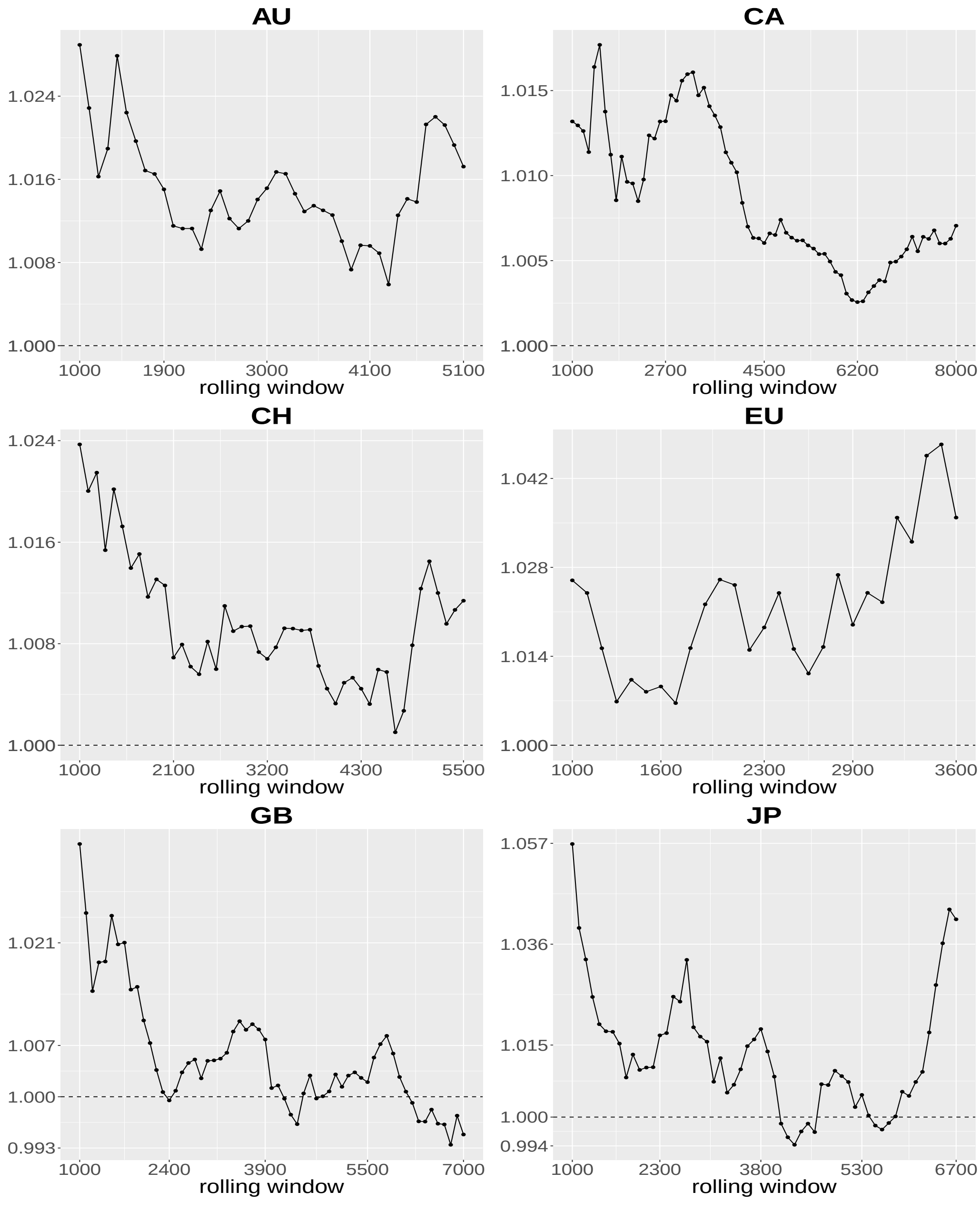
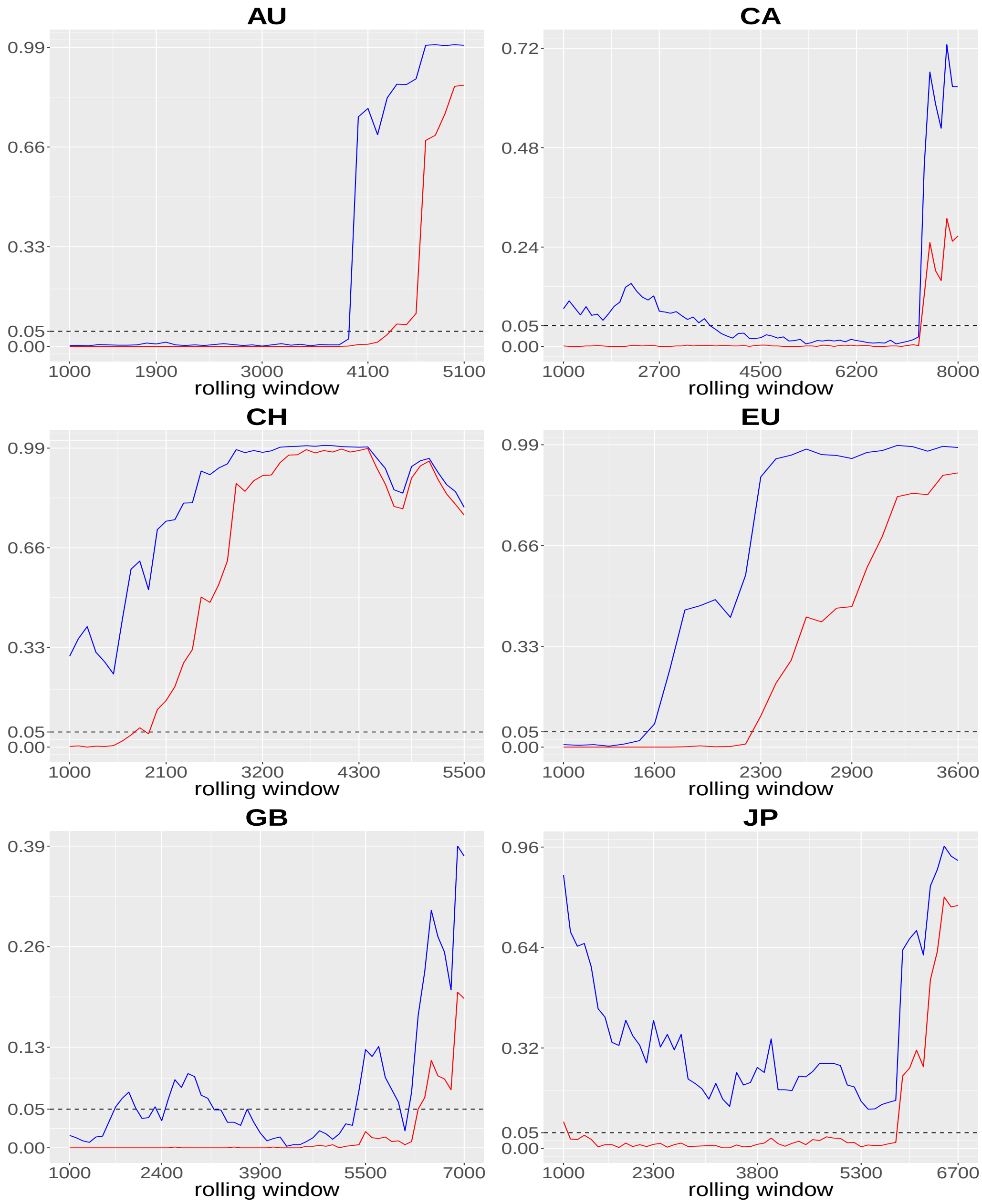
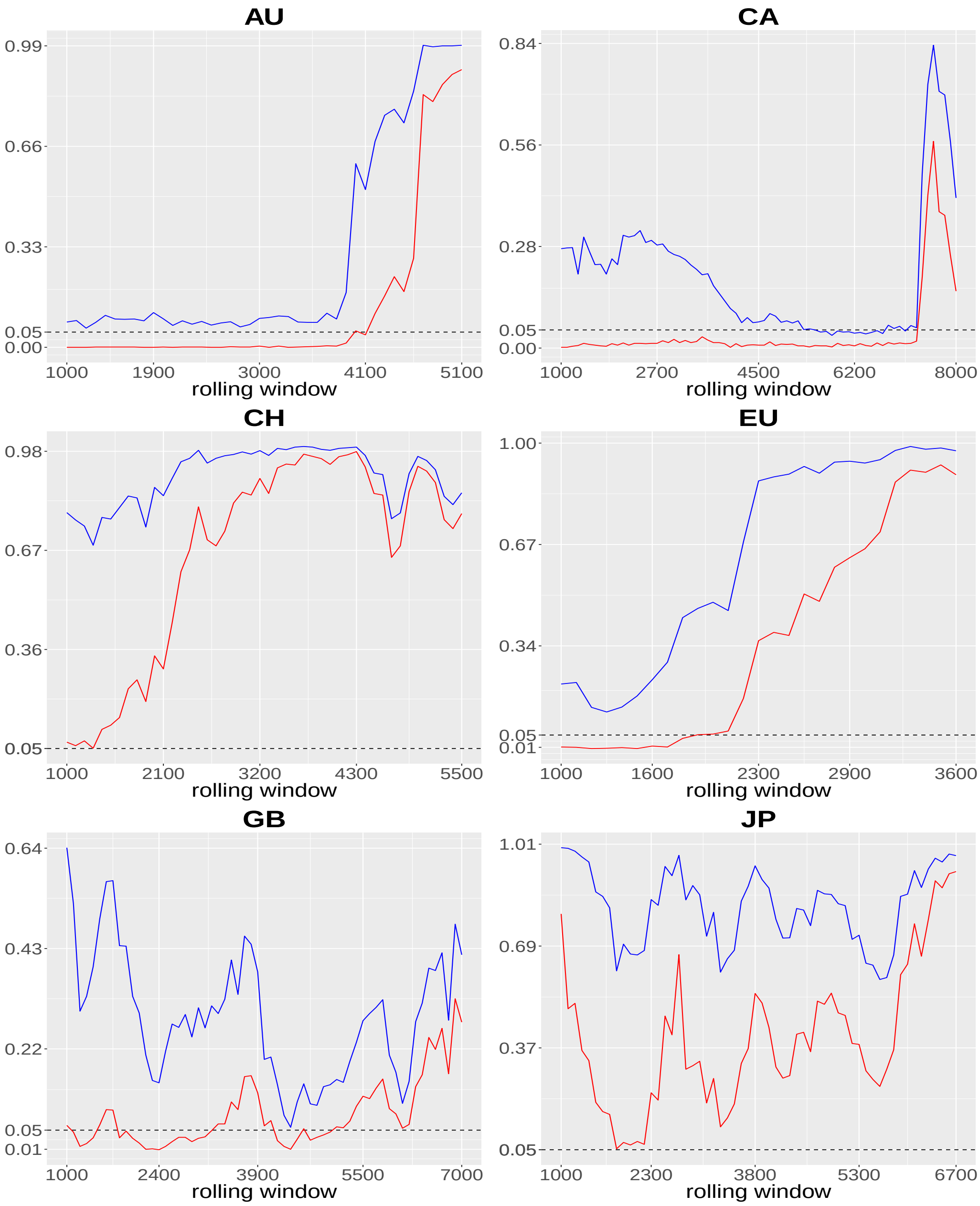


Figure 8: The Rolling Window Width and its Corresponding MSPE Ratios (h = 20)



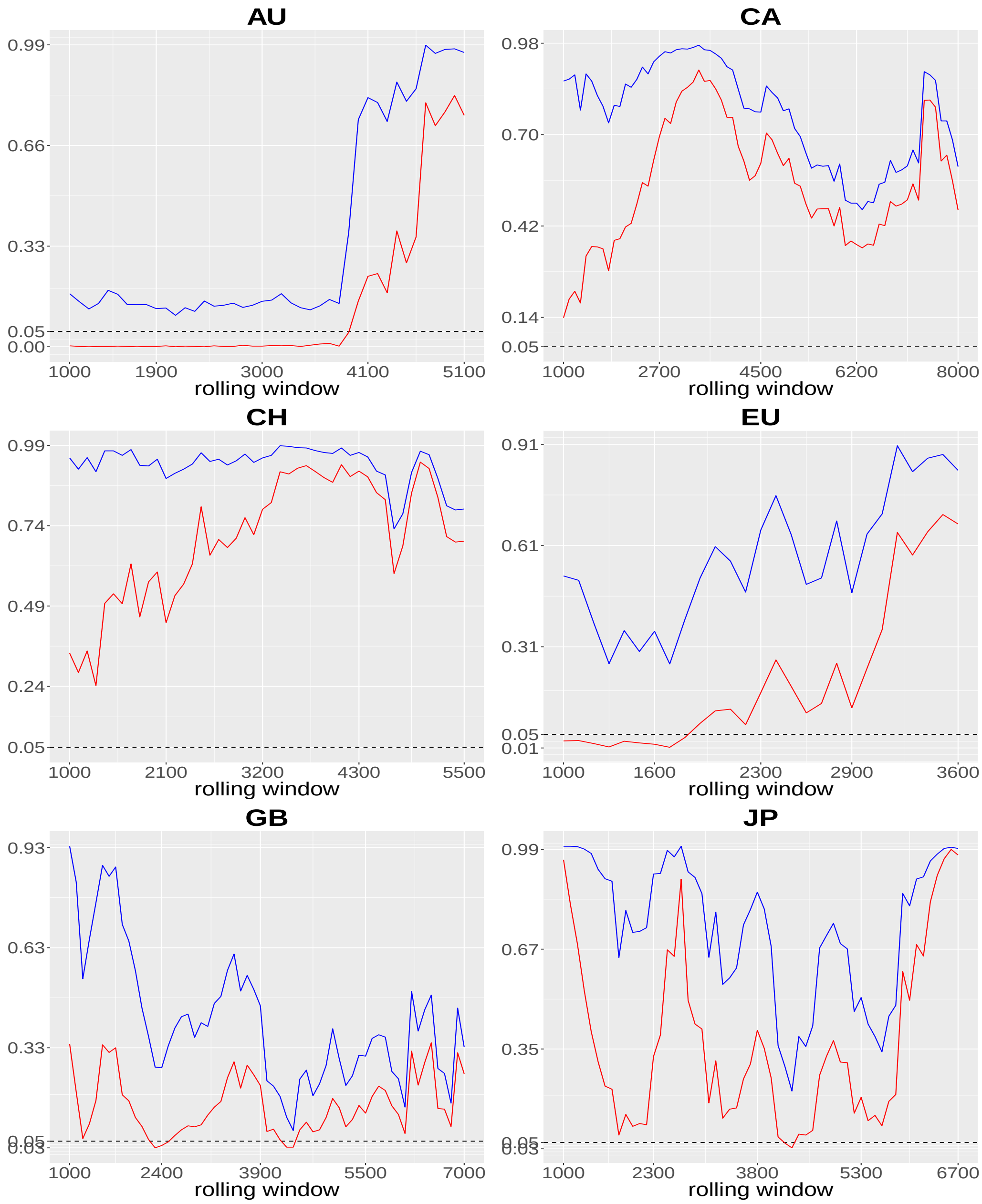
Note: The blue line and red line denote the bootstrap P-value of the test suggested by Diebold and Mariano (1995) and the Clark and West (2007), respectively.

Figure 9: The Rolling Window Width and its Corresponding P-values (h = 1)



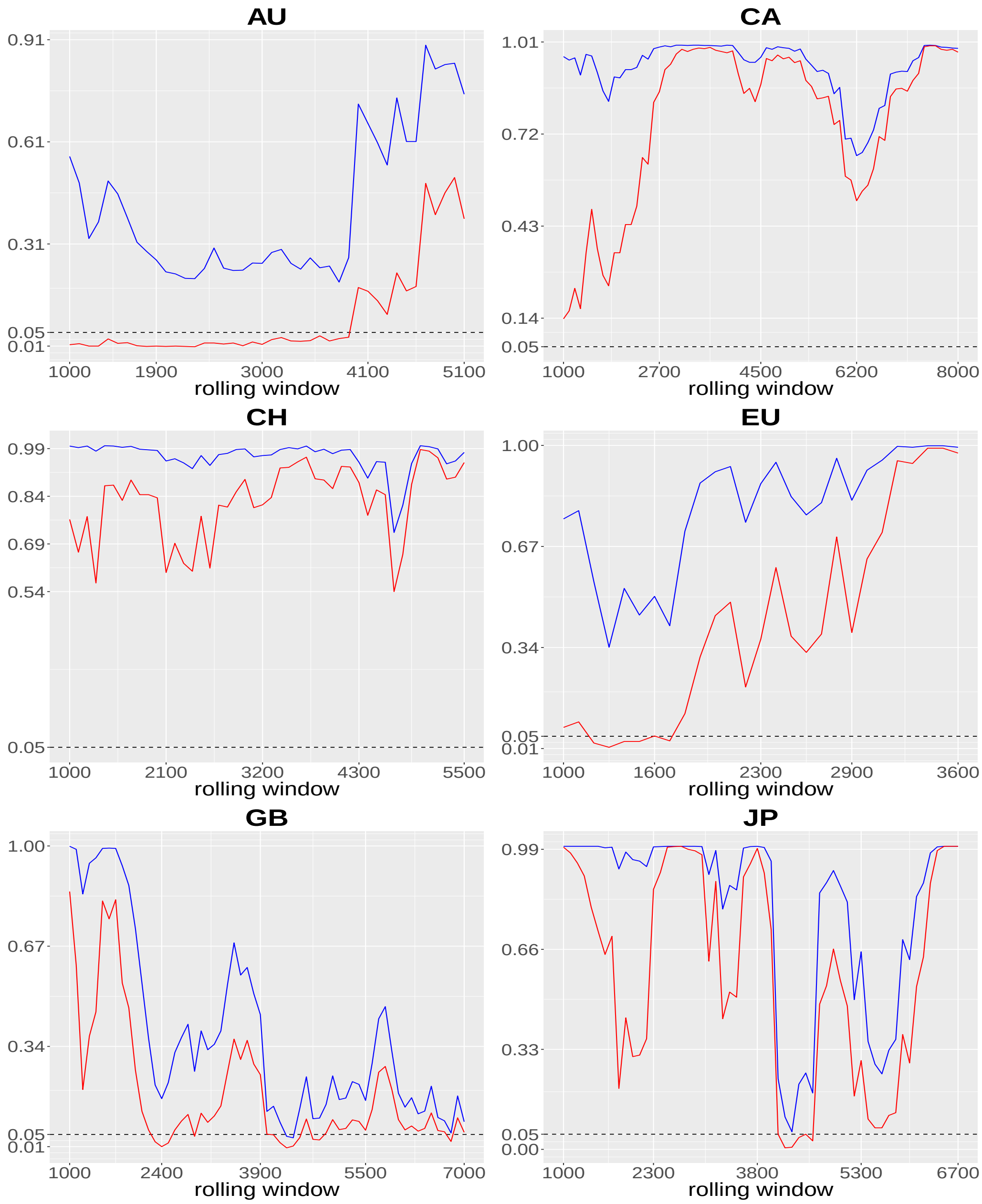
Note: See notes to Figure (9).

Figure 10: The Rolling Window Width and its Corresponding P-values (h = 2)



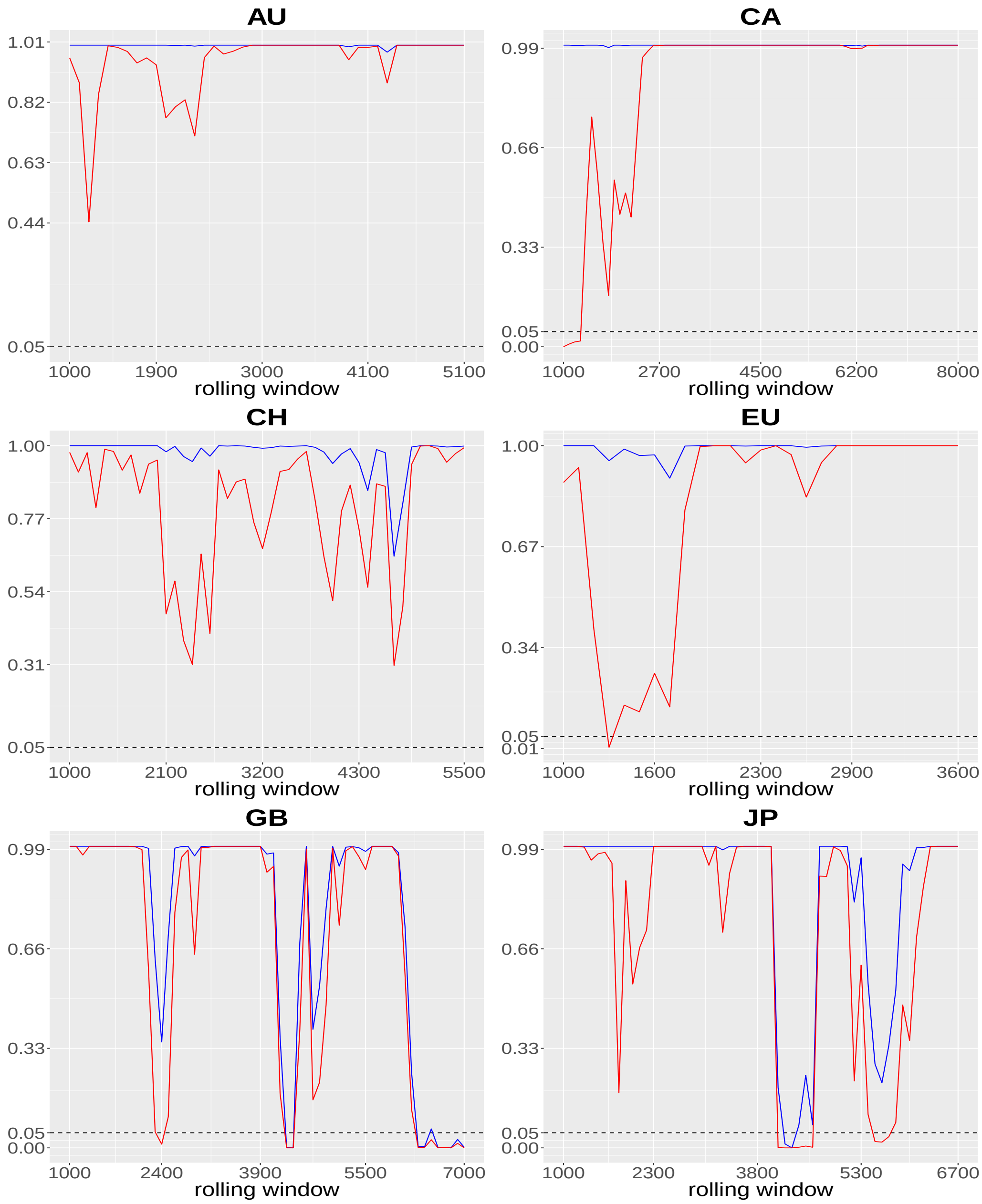
Note: See notes to Figure (9).

Figure 11: The Rolling Window Width and its Corresponding P-values (h = 3)



Note: See notes to Figure (9).

Figure 12: The Rolling Window Width and its Corresponding P-values ($h = 5$)



Note: See notes to Figure (9).

Figure 13: The Rolling Window Width and its Corresponding P-values (h = 20)

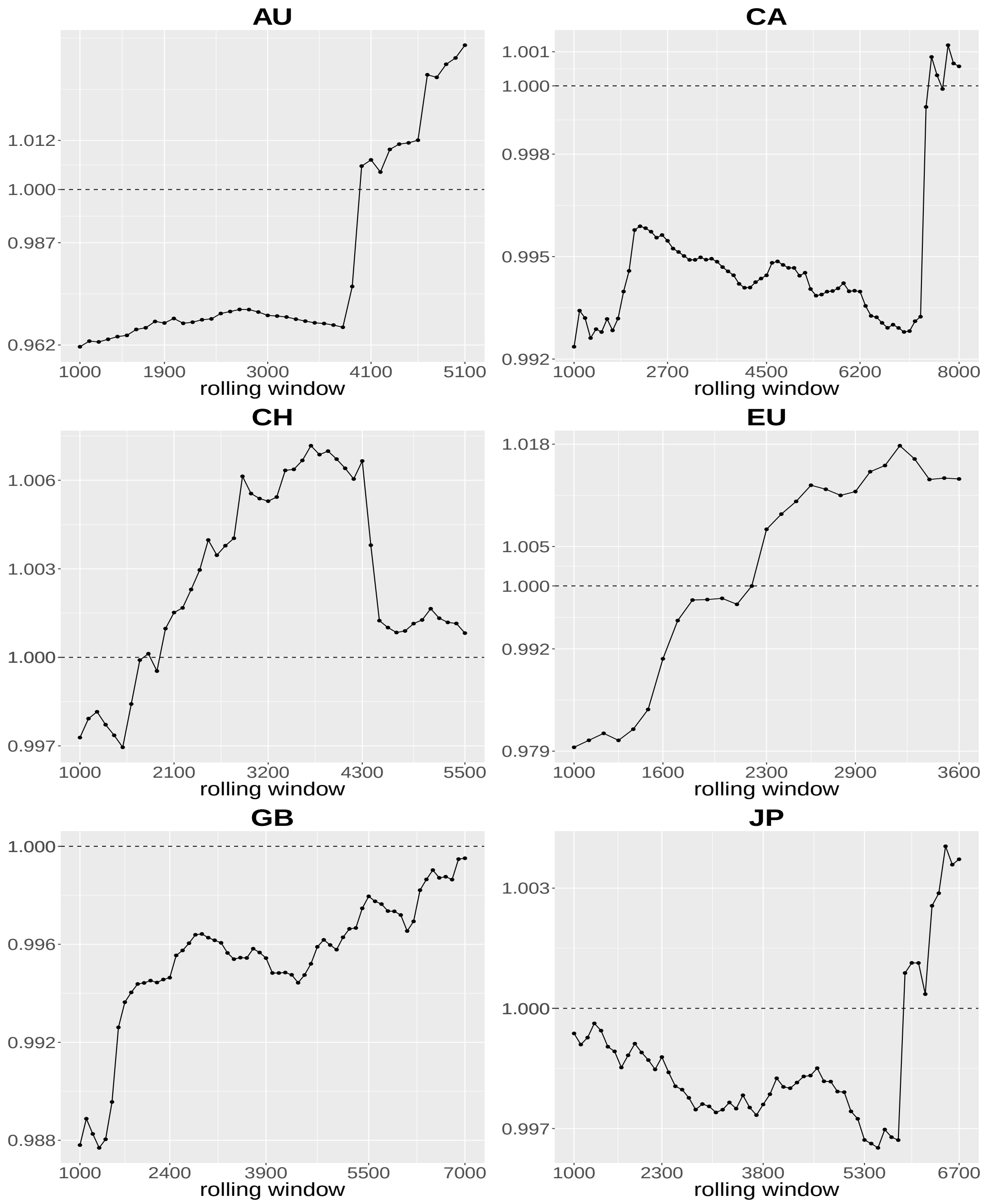
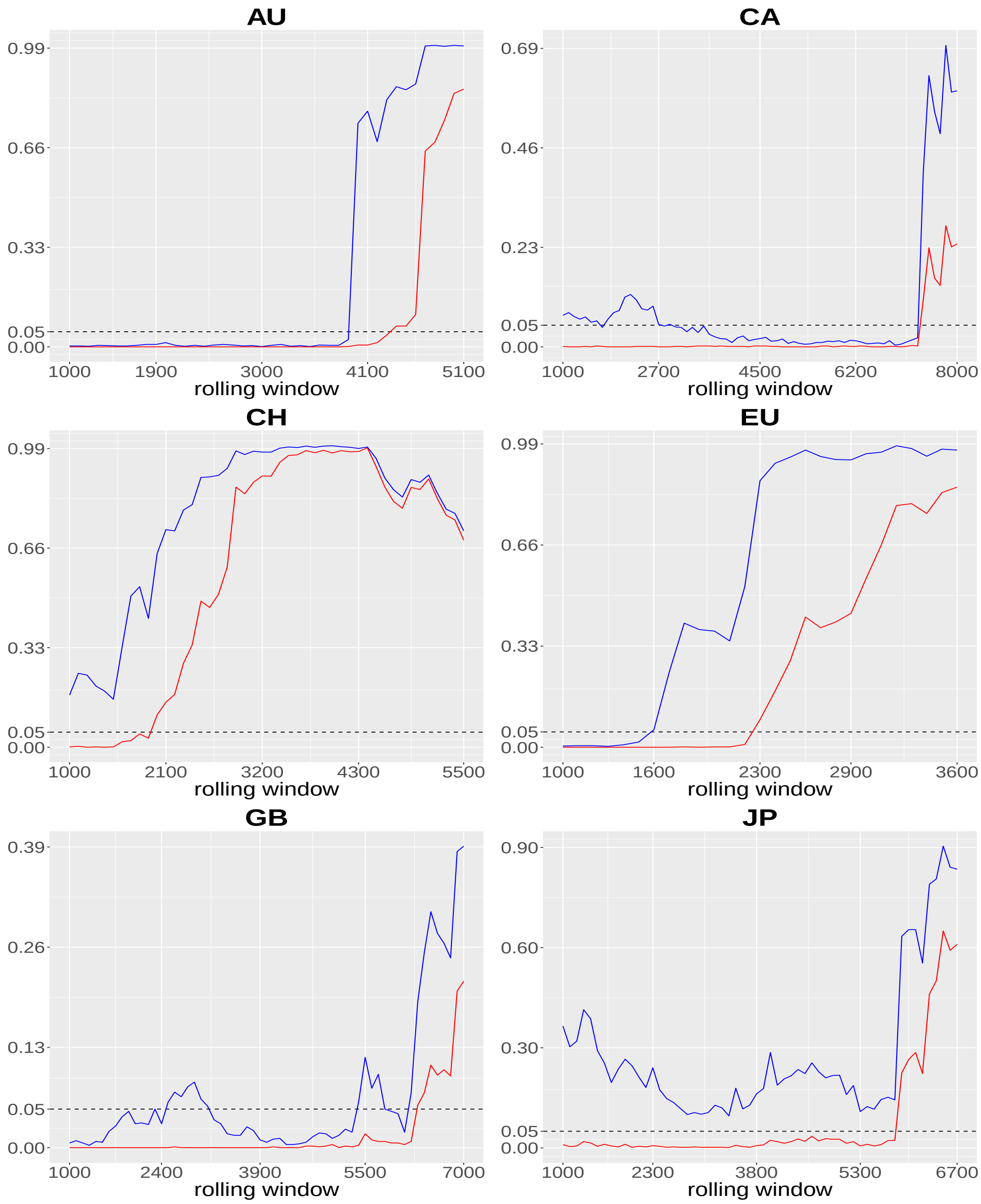


Figure 14: Robustness Check: Using Historical Mean Model as Benchmark. The Rolling Window Width and its Corresponding MSPE Ratios (h = 1)



Note: See notes to Figure (9).

Figure 15: Robustness Check: Using Historical Mean Model as Benchmark. The Rolling Window Width and its Corresponding P-values (h = 1)

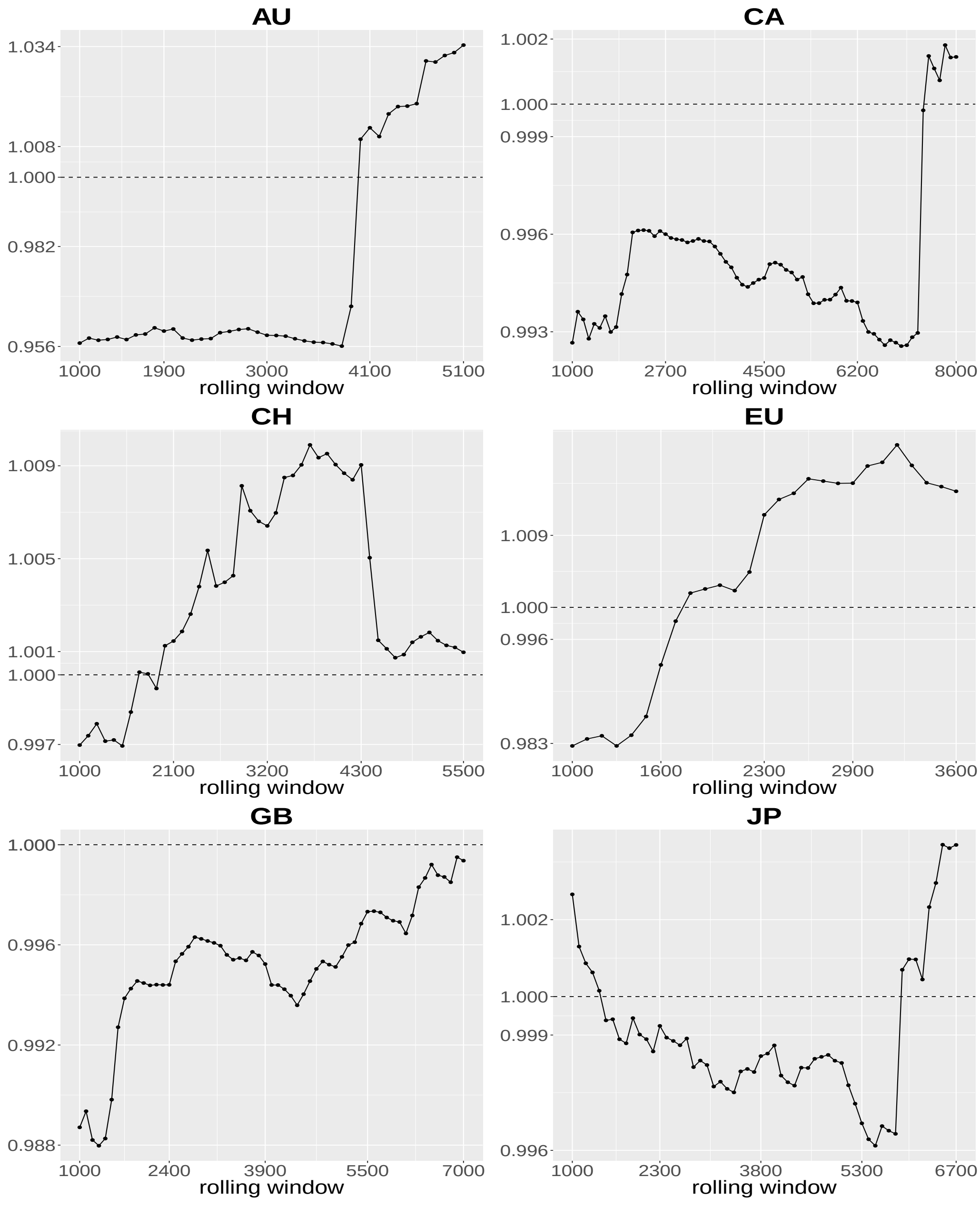
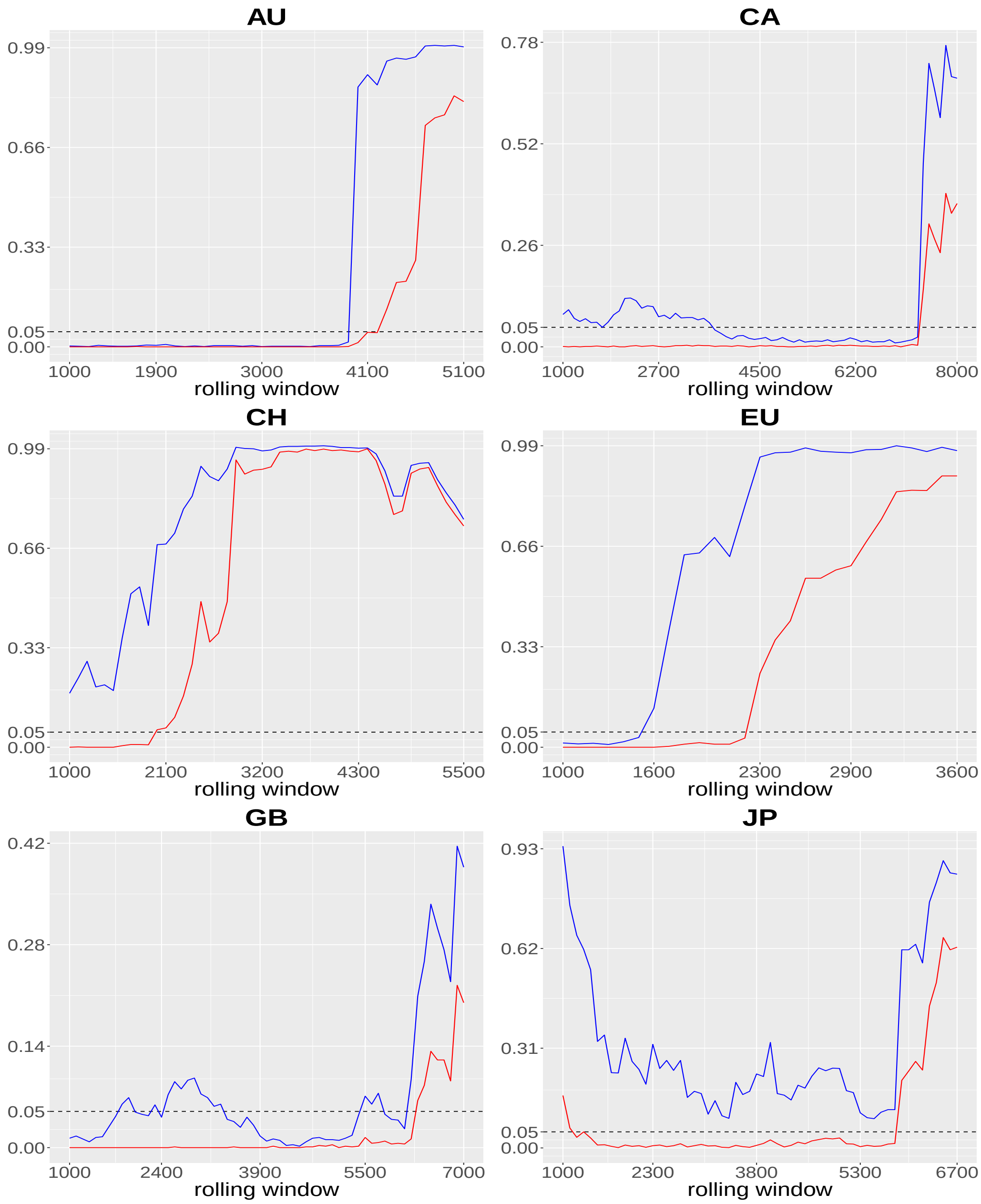


Figure 16: Robustness Check: Forecasting the Level of Exchange Rate. The Rolling Window Width and its Corresponding MSPE Ratios ($h = 1$)



Note: See notes to Figure (9).

Figure 17: Robustness Check: Forecasting the Level of Exchange Rate. The Rolling Window Width and its Corresponding P-values ($h = 1$)

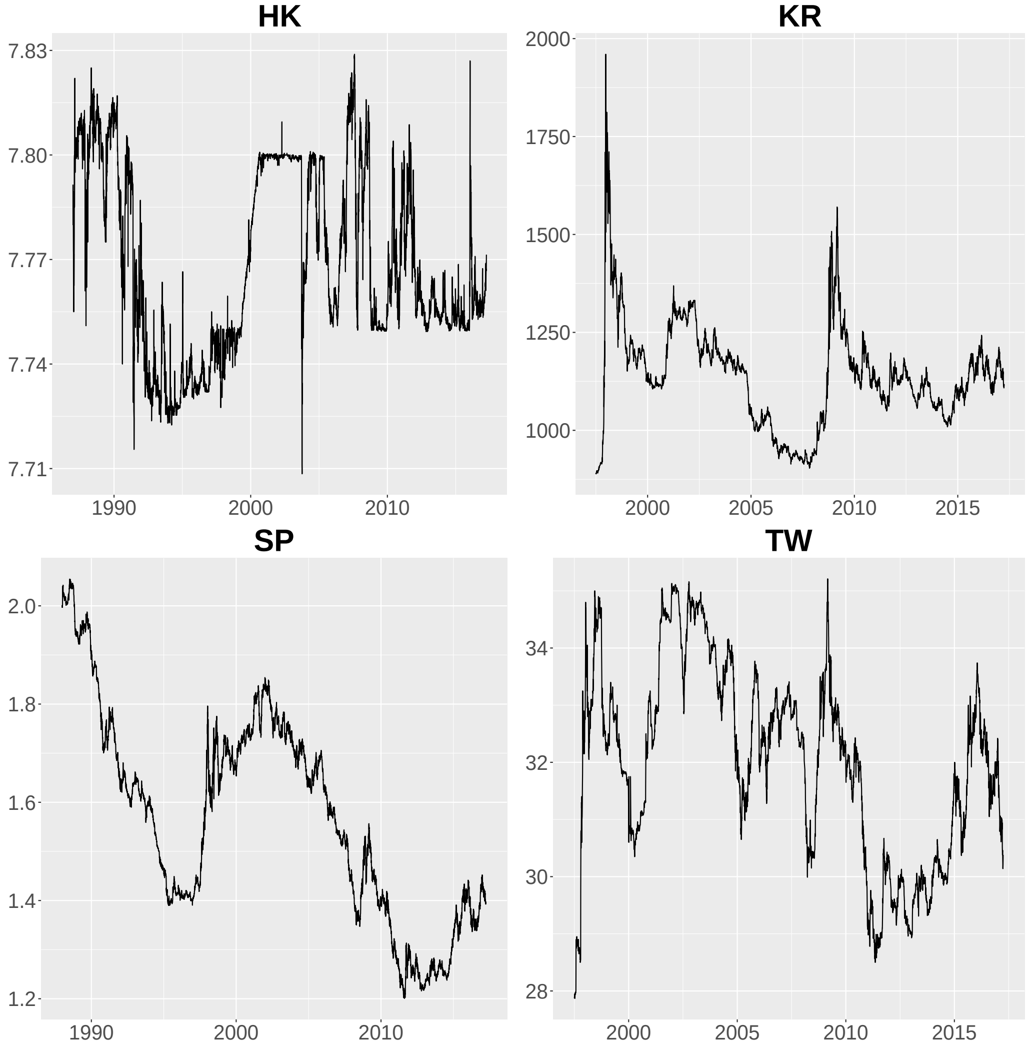


Figure 18: Nominal Exchange Rates of The Four Asian Tigers

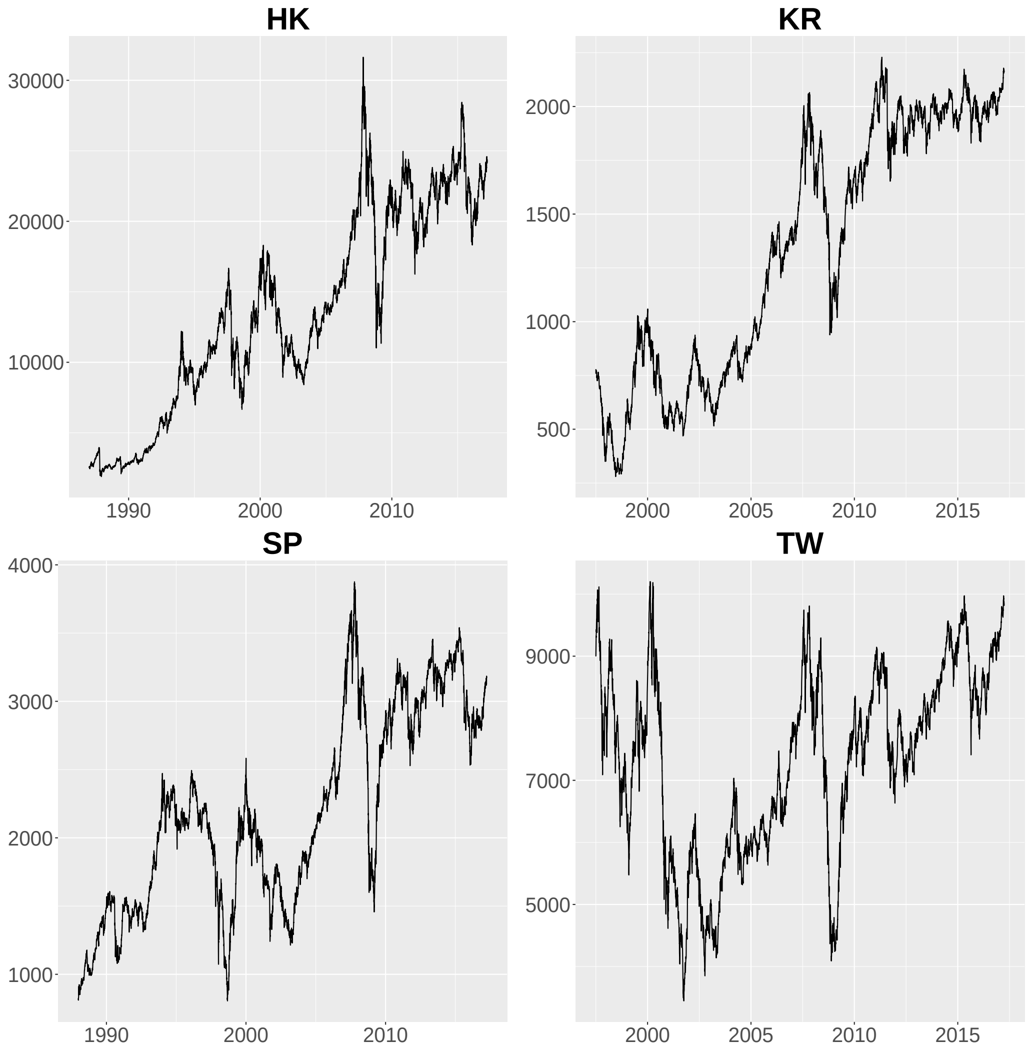


Figure 19: Stock Price Indices of The Four Asian Tigers

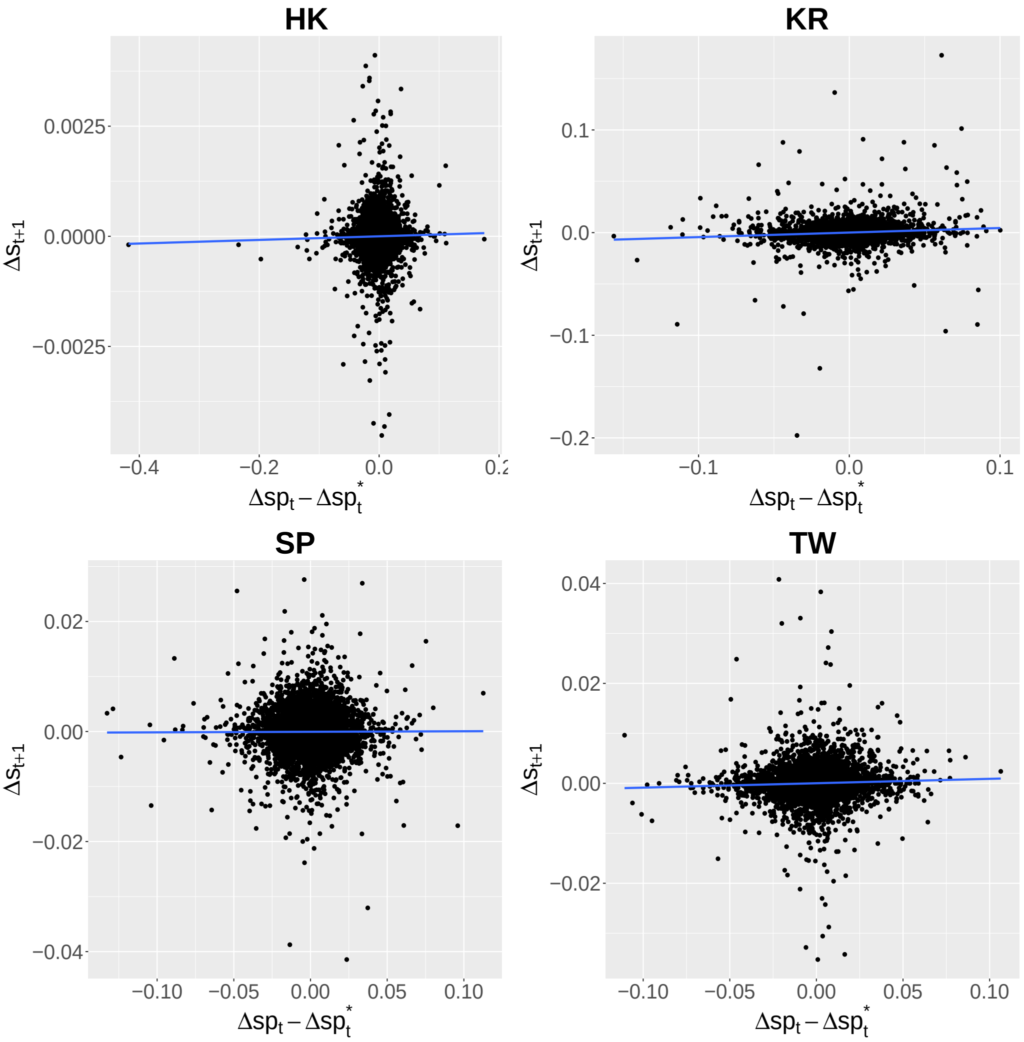


Figure 20: Scatter Diagram of The Four Asian Tigers

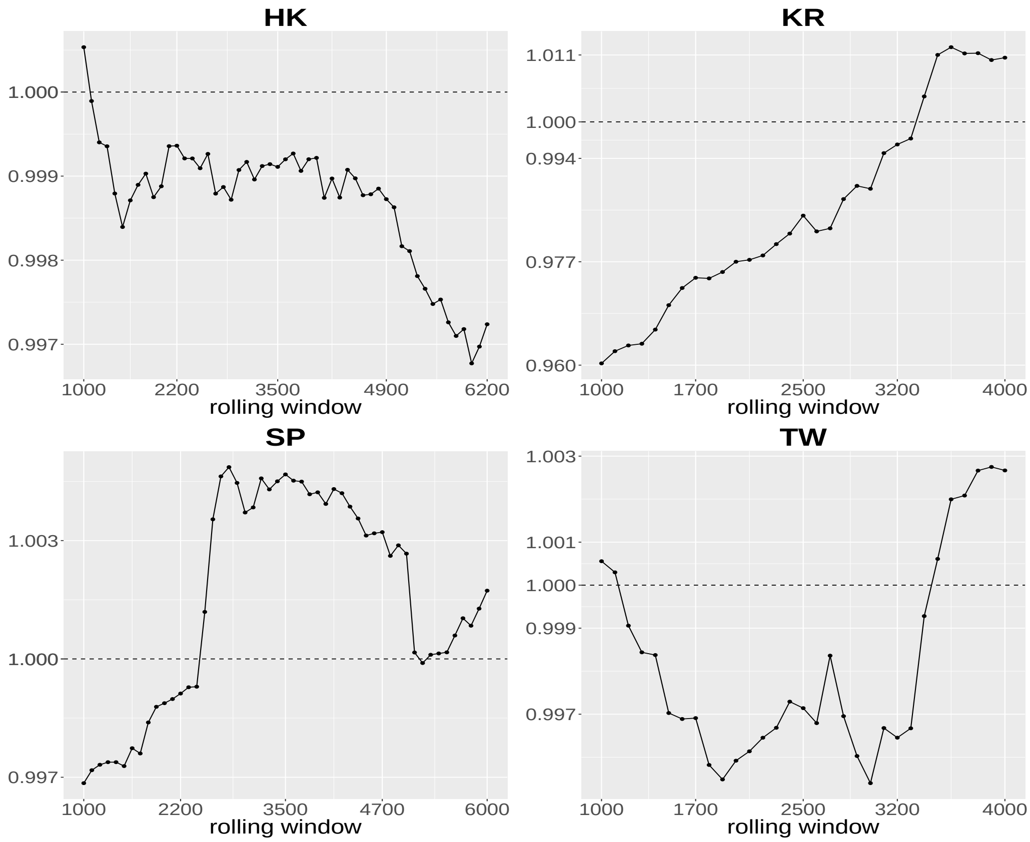
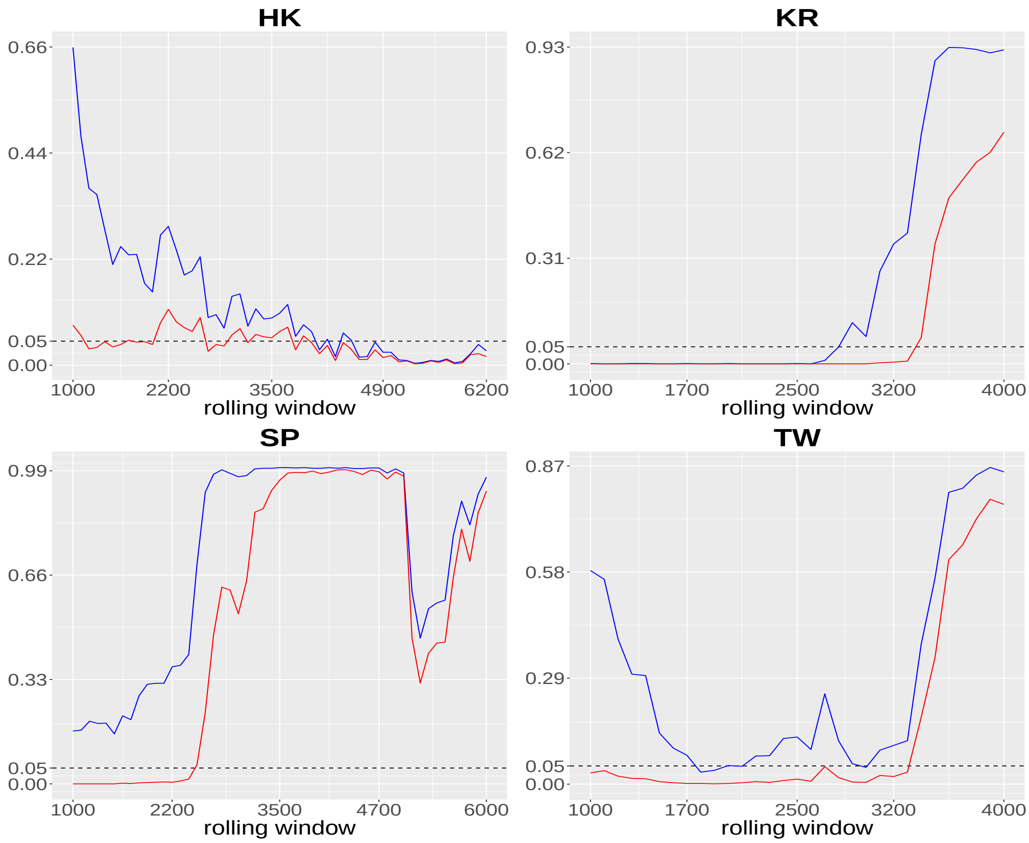


Figure 21: Robustness Check: External Validity. The Rolling Window Width and its Corresponding MSPE Ratios (h = 1)



Note: See notes to Figure (9).

Figure 22: Robustness Check: External Validity. The Rolling Window Width and its Corresponding P-values ($h = 1$)