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The Usefulness of Financial Variables in Predicting Exchange Rate Movements

José Luiz Rossi Júnior

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Insper Institute of Education and Research

ABSTRACT

This paper studies the predictive power of several financial variables usually used as proxies for global liquidity, volatility, and risk aversion in forecasting exchange rates for a set of countries from January 2001 to April 2013. The results indicate that changes in the long-term interest rate, in the VIX, in the high yield spread, and in the market liquidity indicators have strong in-sample and out-of-sample predictive power with respect to exchange rates. The results indicate that the relationship between the financial variables and the exchange rate is relatively stable. The paper shows that the predictability of the models is persistent over time and does not depend on the choice of the window size adopted in the forecasting exercises.

Keywords: Exchange Rates; Liquidity; Volatility; Forecasting.

JEL Classification: *F31; F47.*

[1] Corresponding Author. E-mail: joselrj1@insper.edu.br. Address: Rua Quatá 300 sala 604 – Vila Olímpia – 04546-042 – São Paulo, SP – Brazil. Phone: + 55 11 4504-2437.

1. INTRODUCTION

The body of research dedicated to analyzing the predictive power of exchange rate determination models has reached limited success in forecasting the exchange rate, especially for short term predictions. In a recent survey, Rossi (2013) concludes that the predictability of the exchange rate models depend on the choice of predictor, forecast horizon, sample period, model, and forecast evaluation method.

Most of this literature focused on the role of macroeconomic fundamentals in explaining the dynamics of the exchange rate, but following the 2007-2008 financial crisis, common global factors as liquidity, volatility, and investors' risk aversion were placed at the center of debate with respect to the dynamics of the price of the assets including the exchange rate around the globe. Miranda and Rey (2012) show, for example, that one common global factor highly correlated with the VIX is able to explain a large fraction of the variance of the price of risk of several assets around the world. Although the debate on the topic has been intense, studies of the role of global factors on the dynamics of exchange rates remain scarce.[2]

This paper sheds light on this discussion by analyzing the role of several financial variables in the dynamics of the exchange rate for a set of 27 advanced and emerging countries between 2001 and 2013. We perform in-sample and out-of-sample exercises with several financial variables usually used as proxies for global liquidity, volatility or risk aversion. We examine their predictive power with respect to the trajectory of exchange rates in these countries. In addition to traditional forecasting exercises, we conduct more robust tests that address possible instability in the relationship. We analyze whether the results are robust with respect to the choice of the forecasting period by performing the Giacomini and Rossi (2010) fluctuation test and we also verify the robustness of the results with respect to the choice of the window size by conducting the Inoue and Rossi (2012) test.

The paper shows that movements of several financial variables not only affect a large set of currencies but also have very robust effects over time. We show that the 10-year treasury yield has strong predictive power with respect to exchange rates. The results also indicate that the VIX, usually viewed as a measure of global uncertainty, the high-yield spread, a variable generally used to measure investors' risk appetite, and variables extracted from the common movements of several liquidity indicators used in the financial market have strong in-sample and out-of-sample predictive power with respect to the dynamics of exchange rates. In addition, we find that the role of these

[2] Cairs et. al. (2007) shows that movements on several exchange rates are correlated with global equity and bond volatility. Since the 90s, external factors were placed as one possible fundamental driving the dynamics of the exchange rate. Reinhart et. al. (1993) suggest that external factors were important drivers of the movements of the exchange rate in Latin America during the period.

variables is relatively stable, rendering better result than previous research that focused exclusively on macroeconomic fundamentals.

The present study is organized as follows. The next section reviews the literature related to the study. Section 3 presents the data and discusses the financial variables used throughout the paper. Section 4 describes the exchange rate model adopted in the study and the methodologies used in the in-sample and out-of-sample exercises. Section 5 presents the results of the forecasting exercises. Section 6 concludes.

2. RELATED LITERATURE

This paper builds on and relates to the role of liquidity and volatility in the financial markets and exchange rate forecasting literatures. In the aftermath of the recent financial crisis, several papers have analyzed the role of liquidity and volatility in financial markets. Brunnermeier and Pedersen (2009) build a model in which interactions between funding and market liquidity lead to illiquidity spirals. The authors show that the model can explain empirical regularities with respect to the dynamics of market liquidity, for example, its common movements across markets and securities and its relationship with market volatility. Acharya and Viswanathan (2011) also relate bank funding, liquidity and asset prices. In their model, when financial firms use short-term debt to finance asset purchases, negative asset shocks force such firms to de-leverage, causing the market and funding liquidity to dry up.

Focusing on foreign exchange markets[3], Lustig et al. (2011) find that a ‘slope’ effect can account for much of the cross-sectional variation in average excess returns between high and low interest rate currencies, relating these factors to volatility in the global equity markets. Menkhoff et al. (2012) establish that global foreign exchange volatility risk offers the best explanation of cross-sectional excess returns of carry trade portfolios and that liquidity risk also helps explain foreign exchange expected returns in such portfolios.

By constructing a measure of FX global liquidity, Banti et al. (2012) show that there is a link between liquidity across currencies and that liquidity risk is priced in the cross section of currency returns. Similar results are obtained by Mancini et al. (2013), who also find strong common movements in liquidity across currencies as well as across equity and bond markets. They confirm that liquidity risk has a strong impact on carry trade returns from 2007 to 2009. Banti and Phylaktis (2013) demonstrate that there is a relationship between market liquidity and funding liquidity – traders’ financial constraints. They find that funding liquidity affects two different aspects of FX market liquidity, transaction costs and market depth, and that the relationship is related to the supply and demand for liquidity.

[3] For a more detailed review of the role of liquidity, focusing on foreign exchange markets, see Banti and Phylaktis (2013).

Analyzing the impact of recent FED non-standard monetary policy, Fratzscher et al. (2013) find that U.S. monetary policy has contributed to portfolio reallocation and to changes in the price of risk across the world.[4] Glocker and Towbin (2012) apply a structural VAR to Brazil, focusing on the relationship between liquidity and macroeconomic fundamentals. The authors find that private liquidity shocks dominate public liquidity shocks and that, especially over long time horizons, global shocks dominate domestic ones.

The exchange rate forecasting literature has sought to analyze the predictive power of exchange rate determination models. Since the influential work of Meese and Rogoff (1983), researchers have had difficulty verifying a model that is broadly consistent in predicting exchange rates. Cheung, Chinn, and Pascual (2005) conduct an exercise similar to that of Meese and Rogoff (1983), incorporating models developed during the 1990s and applying new econometric techniques. The authors conclude that some models perform well for certain projections or specific exchange rates, but that none perform well consistently.[5] In a recent survey, Rossi (2013) continues to find this instability in forecasting exchange rates. In particular, she finds that prediction of the exchange rate using economic models depends on the choice of predictor, forecast horizon, sample period, model, and forecasting evaluation method. This limited success in forecasting exchange rates, especially for short-term predictions, is considered one of the major weaknesses of international macroeconomics (Bacchetta and Wincoop, 2006).

In recent years, the literature has focused on different explanations for this instability in forecasting the exchange rate. From a theoretical perspective, one possible explanation for the fragility in forecasting the exchange rate concerns the way the exchange rate is determined. If the exchange rate is the expected present discounted value of current and future fundamentals, it is possible that the evolution of the exchange rate is affected not only by the dynamics of observable fundamentals such as monetary aggregates, the price level, or output, but also by unobservable variables such as risk premia or noise trading. As discussed by Engle, Mark, and West (2008), if these unobservable factors have little correlation with observable factors, this reduces the predictive power of models, leading to the weak results found in the literature.[6]

The idea that common global factors might assist researchers in forecasting exchange rates arose over the last decade with several papers documenting that estimated common factors explain a significant fraction of the variability of exchange rates across a set of countries. The main question

[4] Other papers are Neely (2010), Bauer and Neely (2012), and Chen et al. (2011).

[5] Faust et al. (2003) also observe that most of the work that finds that macroeconomic models outperform a random walk model is sensitive to the choice of horizon and sample period.

[6] Another explanation supplied by Engel and West (2005) is that if the exchange rate is determined by present value deduced from future fundamentals, at least one of the fundamentals possesses a unit root, and the discount factor is near 1, then the exchange rate will behave similarly to a random walk. They argue that within this framework, it would be very difficult for macroeconomic models to outperform a random walk in forecasting exchange rate movements.

that arises concerns identification of the estimated factors. Cayen et al. (2010), using a factor analysis, verify a correlation between commodity prices and common global factors. McGrevy et al. (2012) identify the euro/dollar, yen/dollar, and swiss-franc/dollar exchange rates as the common factors, arguing that the first two account for the two highest volumes of foreign exchange transactions in the spot markets and that the Japanese yen and Swiss franc serve as "safe-haven" currencies in moments of turmoil in the U.S.

Rossi (2012) find that during the 2000s a decrease in market segmentation took place in the commodity markets with this market becoming more integrated to equity markets. In this sense, this paper is also related to the literature that analyzes the predictive power of the price of the commodities in the dynamics of the exchange rate. Examples are Chen et. al. (2010), Chen and Rogoff (2003), among others.

3. DATA

We use weekly data from January 2001 to April 2013. The following countries are used in the analysis: Australia, Canada, Chile, South Korea, Philippines, UK, Israel, Japan, Mexico, New Zealand, Norway, Denmark, Poland, South Africa, Sweden, Switzerland, Turkey, Brazil, Russia, Singapore, Taiwan, Thailand, Peru, Colombia, Hungary, Czech Republic and Indonesia. We use exchange rates recorded at the end of each week. All exchange rates are relative to the U.S. dollar and follow the convention of local currency quantity per unit of foreign currency. All exchange rate and financial variables data are collected from DataStream.

3.1 FINANCIAL VARIABLES

Based on the literature that establishes the existence of a relationship between global factors and the dynamics of the exchange rate we employ in the paper several financial variables not only adopted by the academic literature but also variables that are viewed by market participants as proxies for global liquidity, volatility, or investors' risk aversion. It is important to note that we do not attempt to find the best financial variable for predicting exchange rate movements. The paper attempts to determine which proxy is useful in forecasting the exchange rate and whether its relationship with the exchange rate is stable. By doing that we are improving our understanding with respect to the determinants of the dynamics of the exchange rate by shedding light on the mechanism through which global factors might impact the exchange rate dynamics, departing from the traditional macroeconomic models.

Long-Term Rates: Usually the literature identifies long-term interest rates as proxies for liquidity related to expected future monetary conditions. Following the 2007-2008 financial crisis and the adoption of non-standard monetary policy by the central banks, the dynamics of the long-term rates and its impact on the foreign economies have been placed in the center of the debate among policy makers and academics, especially with respect to the movements that took place in the exchange rate during the period. Fratzscher et al. (2013), for example, find that U.S. monetary policy has contributed to portfolio reallocation and to changes in the price of risk across the world. They found that the impact of U.S. quantitative easing measures on capital flows outside the U.S. have been relatively small compared to other factors in terms of economic significance, yet they exacerbate the pro-cyclicality of capital flows. They also found a significant impact on asset prices. They attribute about one third of the overall depreciation of the U.S. dollar during the 2007-11 period to the unconventional policies. Turner (2013) also argues that movements in long-term rates affect the domestic aggregate demand, but also affect global capital flows, debt accumulation especially in emerging markets, and global financial risk. Krishnamurthy and Jorgensen (2011), Gagnon et. al. (2010), among others show that the quantitative easing policies have an impact on long-term bonds and interest rates. We add then the U.S. 10-year treasury yield as our proxy for long-term interest rates (T10Y) with the objective of analyzing its predictive power on the exchange rate.[7]

Mancini et al. (2013) find a positive relationship between both the VIX and the TED spread measures and FX market liquidity for the most commonly traded currencies during the financial crisis. Using the VIX and a composite volatility index, Cairns et. al. (2007) found that in periods of high volatility, high-yielding currencies tend to depreciate while low-yielding ones tend to serve as a "safe haven". Therefore, we analyze the predictive power of the VIX and the TED spread for the dynamics of the exchange rate.

The High Yield spread (HY) - The spread between non-investment grade and investment-grade corporate bonds, a variable used by market analysts as a proxy for investors' risk aversion is also used in the analysis. The lower the spread, the higher is investors' risk appetite. It is interesting to note that despite its common use as a measure of investors' risk aversion, studies focusing on role of the high yield spread in predicting other variables are inexistent. We use then this variable to analyze its relationship with the exchange rates.

One alternative to the use of several indicators would be to attempt to identify global liquidity through their common movements. Eickermeier et al. (2013) measure global liquidity using common global factors in the dynamics of different liquidity indicators, based on a panel of 24 countries. They find that global liquidity is driven by three main factors: global monetary policy, global credit supply, and global credit demand. In addition, Chen et al. (2012) use the common movements of a set of assets to capture the costs of noncore liabilities. They construct an index of liquidity, extracting the common movements of these assets. Instead of estimating a common factor for liquidity, we use

[7] Another possible concern would be that we use U.S. based measures instead of global measures. Bierut (2013) shows that G5 aggregates outperform global liquidity measures. Since our exchange rates are relative to the U.S. dollar, we do not expect significant changes in the results when global measures are adopted. In addition, with this choice we are not required to address problems associated with aggregating the various measures over different countries, which is not an easy task.

a market based index, the Merrill-Lynch Global and Emerging Markets liquidity index, to verify whether the dynamics of common factors embedded in a set of liquidity indicators have predictive power with respect to exchange rates.

This index is estimated from a panel of spreads, asset prices, and monetary and credit data. The global index (ML) is a composite index, combining data from the U.S., the Euro area, Japan, and emerging markets. The sub-indexes are aggregated into the global index, based on weights calculated according to market capitalization and private sector credit. The Emerging Markets Index (MLE) follows the same procedure, but uses data from 10 emerging market countries.

Table 1 shows the correlation among the different variables used in this paper. In general the results in table 1 indicate that with the exception the correlation between the T10Y and the TED spread, all other correlations are relatively high among the variables. The VIX, the High yield spread, and the two market liquidity index show a correlation superior to 0.60. It is interesting to point out that the VIX shows a correlation above 0.50 with all variables except with the T10Y.

4. EXCHANGE RATE MODEL AND METHODOLOGY

The following exchange rate determination model is adopted as our baseline specification:

$$\Delta S_{i,t} = \alpha_i + \beta_i . \Delta FV_t + u_{i,t} \tag{1}$$

Where $\Delta S_{i,t}$ represents changes in the (log-) nominal exchange rate for country i, ΔFV_t are the changes in one of the financial variables adopted in the text and $u_{i,t}$ is the error-term.

Rossi (2013) discusses several aspects of the estimation of exchange rate models, leading us to focus on models such as (1) to analyze the usefulness of the different financial variables.

First, note that we use a single-equation, realized fundamental model. Therefore, realized fundamentals are used to forecast the exchange rate. Although exercises using models like (1) are not truly out-of-sample exercises (as it uses information not available to the forecaster at time t), as discussed by West (1996) and Ferraro, Rogoff and Rossi (2012), this kind of models are useful when the researcher is not interested in the ex-ante prediction but in evaluating the predictive power of an unmodelled variable, which is exactly the case here, where we try to verify the predictive power of the financial variables. Moreover, Rossi (2013) concludes that the choice of a lagged or contemporaneous specification does not significantly affect the final result.[8]

Another possibility noted by Rossi (2013) is the use of error correction models. Since conventional tests usually do not reject the presence of unit roots in variables, one could use a model in levels instead of differences (error-correction models). Ferraro, Rogoff and Rossi (2012) argue that error-correction models provide more gains at lower than at higher frequencies. Given that exchange rate forecasting is more difficult at higher frequencies, we prefer to use models such as (1).

[8] Ferraro, Rogoff and Rossi (2012) enumerate several examples of analysis that perform similar exercises.

In addition, Chen, Rogoff and Rossi (2010) argue that models such as (1) are more appropriate than error-correction models when one is not testing a specific model, but rather testing only the predictive power of a variable, which is what we are attempting here with respect to financial measures.[9]

Adrian et al. (2010) analyze the role of funding liquidity, using panel techniques to forecast exchange rate movements. In the present paper, by contrast, we use a country-by-country specification to analyze the role of the financial variables, as we expect that these variables play different roles in different countries, a possibility we will investigate.[10]

In choosing the frequency of the sample, the researcher faces a trade-off between frequency and the span of the data. As all variables are available weekly, and the period of estimation, 2001–2013, is sufficiently long for all predictability tests, we have chosen to use weekly data. Moreover, since short-term predictability is the Achilles' heel of forecasting the exchange rate, we focus on weekly frequency data. However, we verify the robustness of our results by analyzing the forecasts using longer frequencies.

4.1 FINANCIAL VARIABLES AND EXCHANGE RATE PREDICTABILITY

To test the predictability of exchange rate models, two types of tests are typically performed in the literature: in-sample and out-of-sample tests. As discussed in Chen, Rogoff, and Rossi (2010), the two types of tests frequently produce different results. The results of such tests depend on several factors, for example, the stability of the parameters and the sample size, among others. The authors observe that in-sample exercises have the advantage of using the full sample size, exhibit higher power if the parameters are constant, and are more effective in detecting predictability. On the negative side, such exercises are more prone to overfitting than out-of-sample tests and sometimes fail to achieve levels of predictability that are characteristic of out-of-sample tests. By contrast, out-of-sample exercises are more realistic and more robust to time variation and misspecification problems. In view of these observations, we conduct both types of exercise, with the objective of analyzing the predictive power of the different financial measures in explaining the exchange rate dynamics.

4.1.1 IN-SAMPLE TESTS

We perform several in-sample tests. Initially we estimate (1) country-by-country for all variables. The estimated coefficients together with the R^2 statistic of the regression are used to analyze the predictive power of the different indicators. Following Fratzscher et al. (2012), we perform a test to analyze the market timing capability of the models. The hit ratio test (HR) shows

[9] Chen and Rogoff (2003) discuss difficulties in using error-correction models to test exchange rate models. In addition to error correction models, Rossi (2013) discusses the use of non-linear and time-varying parameter models. She argues that such models have had mixed success.

[10] Cairns et. al. (2007) show the heterogeneity in the relationship between global volatility and exchange rate.

the percentage of correct estimations by the model of realized changes in the exchange rate. Several authors (Chen, Rogoff and Rossi (2010) and Rossi (2006, 2012), among others) argue that the difficulty in modeling the dynamics of the relationship between the exchange rate and macroeconomic fundamentals is that, for various reasons, this relationship is unstable over time. Rossi (2005) discusses the failure of the conventional Granger-causality test in the presence of these instabilities. To analyze this problem, we test whether the financial measures Granger cause the exchange rate for all countries in the sample. In addition to the traditional Granger-causality test, we conduct Rossi (2005) Granger-causality tests, which are robust to the instabilities noted above.[11]

4.1.2 OUT-OF-SAMPLE TESTS

We follow Ferraro, Rogoff and Rossi (2012) and conduct a rolling windows "out-of-sample" forecasting exercise, using equation (1). Chen, Rogoff and Rossi (2010) argue that the rolling window scheme is more robust with respect to possible time-variation of the parameters because it adapts more quickly to possible structural changes than a recursive scheme does.

Inoue and Rossi (2012) discuss difficulties that arise in the determination of window size. Larger windows would be chosen if the data generating process is stationary, but the cost of adopting larger windows implies that we have a lower number of observations to verify the predictive power of the model. Shorter windows are more robust to breaks, but allow for less precise estimations of parameters. In addition, Inoue and Rossi (2012) argue that the choice of window size might induce the researcher to data-snoop, i.e., seek a window size that is most beneficial to the model. To avoid these problems, we obtain our baseline results from a window of size N=T/2 (half of our sample size) and use the Inoue-Rossi test (2012) to verify the robustness of the results. In this test, we evaluate the predictive power of the models over a range of window sizes.

The out-of-sample forecast is performed for four different forecast horizons (h=1, 2, 4 and 8 weeks ahead). To evaluate the performance of each model, we use the ratio of the root mean square prediction error (RMSPE) of each model to the root mean square prediction error of the benchmark model.

At this point, however, an important issue arises with respect to the evaluation of the model. In general, two benchmarks are used in the literature: the random walk with and without a drift. Rossi (2013) argues that the choice of the benchmark model is crucial to the results and that the random walk without drift is the toughest benchmark to beat. In this paper, accordingly, we use the

[11] Granger-causality tests are consistent with the view that the exchange rate is determined by the present value of future fundamentals, making the test useful for analysis of the predictive power of financial variables. If changes in global liquidity, volatility, or risk aversion represented for the financial variables have any predictive power with respect to exchange rate movements, one should fail to reject the hypothesis that the proxies Granger cause exchange rate movements.

results for the random walk without drift as our benchmark. However, the results for the random walk with drift are available upon request; they are not presented here to save space.

A ratio between the root mean square prediction error (RMSPE) of a given model to the root mean square prediction error of the benchmark model below 1 indicates that the model possesses a RMSPE smaller than that of the random walk model. However, even a value above 1 can be viewed as evidence of superior performance of the model compared with the random walk. As argued in Clark and West (2006, 2007), if the process generating the exchange rate is in fact a random walk, the inclusion of other variables should introduce noise into the forecasting process, leading to a mean square prediction error that is, on average, greater than that of the random walk (and thus producing statistics with values greater than 1).

We then use the Clark and West (2006) statistic as the evaluation criterion of forecast quality. The Clark and West statistic (2006) is more appropriate than those of Diebold and Mariano (1995) and West (1996) (DMW) for asymptotic tests of nested models. As observed by Clark and West (2006), in nested models, the DMW statistics yield a test statistic with a non-normal distribution, leading to underestimation of the number of null hypothesis rejections.

The out-of-sample analysis must also address possible instability observed in the literature in forecasting exchange rates. The usual statistics compare the predictive power of the model over the whole sample. Given the instability of exchange rate models, it is possible that a model cannot consistently beat the benchmark over the entire period but outperform the benchmark over some portion of the sample period.

Rossi (2013) observed this behavior in traditional macroeconomic models. We therefore use the fluctuation test developed by Giacomini and Rossi (2010) to address such instability. In this test, a measure of relative local forecasting performance of two models is estimated, and at each point in time, the models are tested to determine which model shows superior forecasting performance.[12]

5. RESULTS

Table 2 shows the results of the tests for the long-term (10 years) treasury yield. The results in table 2 indicate a strong relationship between the long-term interest rate and the exchange rate. The coefficient of the long-term interest rate variable in the estimation of (1) is statistically significant for 15 of the 27 countries in the sample. It is interesting to point out that results of the in-sample exercise confirm the heterogeneity of the impact of changes in the long-term rates. While the Japanese yen and the Swiss franc appreciate for increases in the 10-year treasury yield, the other currencies depreciate, with the Brazilian Real being the more sensitive currency to changes in the long-term rates. In addition, the Granger-causality test rejects the null hypothesis of non-causality for

[12] Both the Inoue-Rossi (2012) test and the Giacomini-Rossi (2012) test are shown considering h=1 week ahead forecast. Other results are available upon request.

a similar number of countries, a strong indication that movements in the long-term interest rate precede movements in the exchange rate. The results are even better when we consider the Granger-causality test that is robust to instabilities, with the null hypothesis now rejected for 20 countries in the sample.

The results of the out-of-sample tests are also promising, with the 10-years treasury yield showing very high predictive power with respect to the exchange rate, a result that is independent of the forecasting horizon considered. For approximately two-thirds of the countries in the sample, the model incorporating the treasury yield outperforms the random walk model. Figure 1 shows the results of the Giacomini-Rossi (2010) fluctuation test. The test analyzes the performance of the model over time. Values above the critical value indicate that the model displays predictive ability. Figure 1 indicates that for most countries where the long-term rate has a predictive power, this power is not concentrated in a brief period of time but for long periods, indicating a robust relationship between the 10-year treasury and the exchange rate. Results displayed in figure 1 are even more pronounced for the most recent years, notably after 2011.[13] Figure 2 confirms that the relationship is also robust to the window size chosen, based on the Inoue and Rossi (2012) test. Again, statistics above the critical value indicates predictability for that window size. Results in figure 2 show that the predictability of the treasury is not the result of the window size chosen to perform the exercise. Predictability shows up for several window sizes.

The results displayed in Table 3 and figures 3 and 4 indicate a very strong and stable relationship between the VIX and the exchange rate for almost all countries. The results of the in-sample exercises show that the estimation of (1) using the VIX as the explanatory variable present coefficients that are statistically significant for all countries but Switzerland. Again, the results indicate heterogeneity in the impact of the changes of VIX on the different exchange rates. The coefficients vary from -0.023 for the Japanese yen until 0.074 for Turkey. Results in table 3 show that the R^2 of estimation of (1) using the VIX as our proxy reach values above 10%, a remarkable result for exchange rate models. Considering the HR test, the model predicts exchange rate changes correctly in 56% of the time. The Granger-causality tests reject the null of non-causality for all countries for the VIX at 10% as our level of significance adopting the test robust to instabilities.

These strong results are maintained when we analyze the out-of-sample exercises. When we consider a forecast horizon of one week the model is able to beat the benchmark for all countries except Switzerland. Although results in table 3 point out that the VIX has very high out-of-sample predictive power, especially for short periods, results also show that this predictive power falls when we consider longer forecasting horizons. Considering a 8-weeks ahead forecasting, the VIX

[13] The fluctuation test is implemented with m=1/2 and 5% level of significance. For details, see Giacomini and Rossi (2010).

outperforms the benchmark for only 14 countries. Results in figure 3 confirm the predictive power of the VIX. The results of the Giacomini-Rossi (2010) test show that the VIX has predictive ability for almost all periods and countries. Figure 4 also indicates that the results are robust with respect to the choice of the window size using the Inoue-Rossi (2012) test.

Table 4 shows the results for the TED spread. Results in table 4 indicate a weak predictive power for the variable. Considering the in-sample exercises, only 8 countries show a coefficient that is statistically significant yet the Granger-causality test robust to instabilities show signs of predictability. The test rejects the null of non-causality for 21 countries in the sample for a 10% level of significance. The out-of-sample exercises presented in table 4 show that for a 1-week forecasting horizon the model is able to beat the benchmark for six countries. The best result for the model is shown for a 4-weeks forecasting horizon when the model is able to outperform the benchmark for 11 countries. The Giacomini-Rossi (2010) test displayed in figure 5 confirms that the TED spread has a very restrict predictive ability concentrated in brief periods of time and countries. The Inoue-Rossi (2012) test in figure 6 also indicates a weak and unstable relationship between the TED spread and the exchange rates.

Different results are shown in table 5. Results in table 5 indicate that the High Yield spread present a strong predictive ability with respect to the exchange rate. With the exception of Switzerland, the estimation of (1) using the High Yield spread result in coefficients that are statistically significant. Again, the coefficients indicate heterogeneity in the impact of change in the high yield spread with countries like Brazil and Australia being the most sensitive countries to changes in the spread. Again, the R^2 of the estimation of (1) reaches values sometimes superior to 20%, a solid result for exchange rate models. The Granger-causality test reject for all countries that the HY does not Granger cause the exchange rate. Results in table 5 also show that the High Yield spread has more consistent predictive power than the VIX, outperforming the benchmark for all countries but Switzerland in one-week ahead, two-weeks ahead and four-weeks ahead forecasting and outperforming the benchmark for 25 countries in eight-weeks ahead forecasting. Figures 7 and 8 confirm a stable relationship between the HY spread and the exchange rate. Figures 7 and 8 show that the results are robust to the period and window size using the respective tests. Although very robust over time, results in figure 7 indicate that the high yield spread had a very significant predictability in the exchange rate right after the financial crisis in the period 2007-2008.

Table 6 and 7 show that use of the dynamics of common movements of several liquidity indicators is useful in forecasting movements of the exchange rate. Both the ML and the MLE indicators have strong in-sample and out-of-sample predictive power with respect to the exchange rate. Focusing on the in-sample exercise, the variables are statistically significant, and the Granger-causality tests show signs of precedence for the liquidity indexes for most of the countries in the sample. The same indications are observed in out-of-sample tests. The liquidity indexes consistently beat the random walk benchmark for almost all countries and forecasting horizons. The results indicate slightly superior performance by the MLE proxy, perhaps suggesting that emerging countries are more susceptible to liquidity shocks than developed ones. The fluctuation test and the Inoue-Rossi (2012) tests not shown for ML index confirm the robustness of the results. One interesting fact that comes from figure 9 is that the liquidity proxy has a superior performance than the benchmark especially right after the financial crisis.

One final remark regarding our results is that we analyze the predictive power of the proxies by examining a set of countries without considering the impact on specific currencies. When we examine more closely the effects on specific currencies one important fact arises: The impact of the financial variables is heterogeneous across countries. The Japanese Yen and the Swiss Franc appear to behave differently than other currencies. The results indicate that factors like changes in global liquidity or volatility has a smaller impact on these currencies than on other currencies, with most proxies exhibiting non-significant relationships with these two currencies. Even when the proxies show some predictive power with respect to these currencies, they tend to impact them in ways that differ from their effects on other currencies. For example, while the VIX and high yield proxies have no impact on the Swiss franc, their impact on the Japanese yen has the opposite sign of their impact on other currencies. It may be that these currencies are viewed as safe-heavens, similarly to the U.S. dollar, in moments of turmoil. On the other side, countries like Brazil and Turkey seem to be highly sensitive to changes in the global environment, with their exchange rate changing significantly with changes in global liquidity, volatility, or investors' risk aversion.

6. CONCLUSIONS

This paper has examined the predictive power of several financial variables usually used as proxies for changes in global liquidity, volatility or investors' risk aversion in forecasting exchange rates for a set of countries from January 2001 to April 2013. Using traditional methods for forecasting the exchange rate and incorporating new methodologies that bring greater robustness to the results, the paper confirms that these variables exhibit both in-sample and out-of-sample predictability with respect to exchange rate dynamics.

Rossi (2013) summarize her results that none of the macroeconomic fundamentals commonly used in the literature show strong out-of-sample forecasting ability across all countries and tests. She argues that macroeconomic fundamentals are only successful in sporadic periods and, therefore, the predictability of the macroeconomic fundamentals is "occasional and short-lived phenomenon". In the paper, we show that our financial variables exhibit a more robust predictive power than the macroeconomic fundamentals.

The point for future research is to analyze what kind of information that is carried in the financial variables that is useful in predicting exchange rate movements. Bekaert et. al. (2013), for example, show that the VIX – one of the variables used in the analysis - is correlated with measures of monetary policy and investors' uncertainty. Therefore, future research should decompose the predictive power of the variables into all components in order to have a better understanding of the determinants of the exchange rate dynamics. In addition, we show that the impact of the financial variables is heterogeneous among the countries. Future research has to analyze whether it is related the way financial markets operate with more liquid foreign exchange markets suffering the most or bad domestic macroeconomic fundamentals are the key to understand the impact of the financial variables.

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Table 1 – Correlation Among the variables

Table 1 shows the correlation among the different financial measures adopted throughout the paper. T10Y is the 10- year treasury yield. VIX is the implicit volatility of the S&P 500. TED is the difference between the three-month LIBOR and the three-month T-bill interest rate. HY is the High Yield spread. ML is the Merrill Lynch Liquidity Index. MLE is the Merrill Lynch Liquidity Index for emerging markets.

	T10Y	VIX	TED	HY	ML	MLE
T10Y	1.00					
VIX	-0.20	1.00				
TED	-0.04	0.52	1.00			
HY	-0.29	0.88	0.43	1.00		
ML	0.33	-0.80	-0.60	-0.93	1.00	
MLE	0.44	-0.69	-0.36	-0.85	0.90	1.00

Table 2 – Results for In-Sample and Out-of-Sample analysis – T10Y

Table 2 shows the results of the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-causality test. GC Robust shows the p-value of the Rossi (2005) Granger-causality test that is robust to instabilities. Table 2 also shows the results of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stand for, respectively, 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

Countries	In-Sample					Out-of-Sample				
	Coeff	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**-2.76***	0.025	51.9%	0.00	0.000	**0.990**	0.000	**0.976**	**0.999**	**0.997**
Canada	**-2.67***	0.048	54.5%	0.00	0.000	**0.997**	0.000	**0.978**	**0.988**	**0.992**
Japan	**4.09***	0.109	60.6%	0.00	0.000	**0.916**	0.000	**0.944**	**0.965**	**0.980**
New Zealand	**-2.78***	0.023	53.3%	0.00	0.000	**0.982**	0.000	**0.997**	**1.000**	**1.000**
Sweden	-0.987	0.003	52.3%	0.22	0.000	**0.996**	0.070	**0.998**	**1.001**	1.005
UK	-1.031	0.007	54.1%	0.16	0.000	**0.999**	0.040	1.002	1.006	1.007
Switzerland	**1.45****	0.010	53.1%	0.04	0.000	1.004	0.300	**0.996**	**0.997**	**1.000**
Norway	-0.984	0.004	52.0%	0.22	0.000	**0.992**	0.010	**0.993**	**0.999**	1.002
Denmark	0.288	0.000	52.7%	0.65	0.000	1.004	0.510	**0.999**	**1.000**	1.004
Israel	-0.900	0.006	54.1%	0.12	0.000	1.002	0.630	1.001	1.003	1.003
Brazil	**-5.67***	0.071	57.8%	0.00	0.000	**0.942**	0.000	**0.979**	**0.988**	**0.996**
South Africa	**-2.42***	0.012	53.4%	0.03	0.000	**0.990**	0.020	**0.997**	**1.001**	**0.997**
Turkey	-1.072	0.001	47.2%	0.37	0.000	1.003	0.270	1.001	1.002	1.003
Russia	**-2.16***	0.039	52.3%	0.00	0.000	**0.973**	0.000	**0.989**	**0.997**	**1.000**
South Korea	**-2.03***	0.023	53.3%	0.00	0.020	**0.991**	0.040	1.002	1.002	**0.999**
Mexico	**-3.11***	0.050	54.5%	0.00	0.000	**0.973**	0.000	**0.990**	**0.992**	**0.994**
Singapore	-0.188	0.001	55.2%	0.57	0.190	**0.995**	0.050	**0.997**	**0.996**	**0.996**
Phillipines	**-0.778***	0.011	54.4%	0.02	0.230	**0.992**	0.010	**1.000**	**0.997**	**0.996**
Poland	**-2.43***	0.016	50.2%	0.01	0.000	**0.988**	0.010	**0.994**	**1.000**	1.002
Taiwan	**-0.679***	0.016	52.7%	0.01	0.040	**0.989**	0.020	**0.995**	**0.998**	**0.996**
Chile	**-2.86***	0.035	50.8%	0.00	0.000	**0.986**	0.000	1.006	1.003	**0.998**
Hungary	-0.798	0.002	48.9%	0.42	0.000	**0.998**	0.013	**0.996**	**0.999**	1.003
Czech	-0.226	0.000	55.6%	0.76	0.000	1.002	0.290	**0.998**	**0.999**	1.002
Colombia	**-1.72***	0.014	54.5%	0.01	0.130	**0.994**	0.020	1.003	**1.000**	**1.000**
Peru	-0.271	0.002	57.7%	0.30	0.180	1.001	0.350	**0.999**	**0.998**	**0.999**
Indonesia	0.039	0.000	46.4%	0.94	0.340	1.005	0.830	1.007	1.008	1.006
Thailand	0.089	0.000	54.2%	0.72	0.580	1.001	0.220	**0.998**	**0.996**	**0.998**

Table 3 – Results for In-Sample and Out-of-Sample analysis - VIX

Table 3 shows the results from the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-causality test. GC Robust shows the p-value of the Rossi (2005) Granger-causality test that is robust to instabilities. Table 3 also shows the results of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stand for, respectively, the 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

Countries	In-Sample					Out-of-Sample				
	Coeff	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**0.049***	0.104	56.6%	0.000	0.000	**0.929**	0.000	**0.986**	**0.997**	**0.998**
Canada	**0.041***	0.144	60.3%	0.000	0.000	**0.897**	0.000	**0.967**	**0.996**	**1.000**
Japan	**-0.023***	0.045	53.4%	0.000	0.000	**0.966**	0.000	**0.997**	**0.994**	**1.000**
New Zealand	**0.056***	0.121	58.3%	0.000	0.000	**0.910**	0.000	**0.986**	**1.000**	1.004
Sweden	**0.034***	0.060	53.0%	0.000	0.000	**0.953**	0.000	**0.991**	**0.998**	1.001
UK	**0.013***	0.013	49.7%	0.000	0.030	**0.990**	0.010	**1.000**	1.008	1.005
Switzerland	-0.003	0.001	52.2%	0.560	0.020	1.002	0.310	1.003	1.001	1.001
Norway	**0.027***	0.038	51.9%	0.000	0.000	**0.960**	0.000	**0.993**	**1.000**	1.001
Denmark	**0.014***	0.014	50.9%	0.000	0.000	**0.983**	0.000	**0.999**	**1.000**	1.002
Israel	**0.028***	0.074	58.4%	0.000	0.000	**0.962**	0.000	1.001	1.008	1.005
Brazil	**0.073***	0.151	62.0%	0.000	0.000	**0.892**	0.000	**0.966**	**0.989**	**0.999**
South Africa	**0.058***	0.088	56.1%	0.000	0.000	**0.917**	0.000	**0.983**	**0.998**	**0.998**
Turkey	**0.074***	0.075	59.4%	0.000	0.000	**0.888**	0.000	**0.983**	**0.999**	1.002
Russia	**0.024***	0.061	54.7%	0.000	0.000	**0.965**	0.000	**0.995**	**1.000**	1.003
South Korea	**0.036***	0.092	57.7%	0.000	0.000	**0.943**	0.000	**0.986**	**0.999**	1.003
Mexico	**0.052***	0.176	60.3%	0.000	0.000	**0.879**	0.000	**0.964**	**0.987**	**0.999**
Singapore	**0.016***	0.077	55.9%	0.000	0.000	**0.939**	0.000	**0.981**	**0.996**	**0.997**
Phillipines	**0.018***	0.070	54.5%	0.000	0.000	**0.946**	0.000	**0.989**	**0.999**	1.002
Poland	**0.053***	0.100	55.8%	0.000	0.000	**0.929**	0.000	**0.987**	**0.995**	**0.999**
Taiwan	**0.010***	0.045	55.8%	0.000	0.000	**0.961**	0.000	**0.992**	**0.998**	**1.000**
Chile	**0.045***	0.114	62.2%	0.000	0.000	**0.935**	0.000	**0.995**	**0.997**	**0.999**
Hungary	**0.050***	0.082	53.6%	0.000	0.000	**0.938**	0.000	**0.988**	**0.996**	**1.000**
Czech	**0.023***	0.026	54.8%	0.000	0.000	**0.976**	0.000	**0.997**	**0.999**	1.001
Colombia	**0.040***	0.094	60.9%	0.000	0.000	**0.951**	0.000	**0.987**	**0.988**	**0.994**
Peru	**0.006***	0.016	58.9%	0.000	0.000	**0.991**	0.000	**0.996**	**0.996**	**0.997**
Indonesia	**0.014***	0.015	50.8%	0.000	0.050	**0.993**	0.030	1.003	1.003	1.004
Thailand	**0.008***	0.017	55.9%	0.000	0.030	**0.987**	0.000	**0.995**	**0.998**	**0.996**

Table 4 – Results for In-Sample and Out-of-Sample analysis - TED

Table 4 shows the results from the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-causality test. GC Robust shows the p-value of the Rossi (2005) Granger-causality test robust to instabilities. Table 4 also shows the results of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stand for, respectively, the 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

	TED									
Countries	**In-Sample**					**Out-of-Sample**				
	Coeff	**R^2**	**HR**	**GC**	**GC Robust**	**1 Week**	**P-Value CW**	**2 Weeks**	**4 Weeks**	**8 Weeks**
Australia	**3.37***	0.052	55.8%	0.030	0.020	**0.982**	0.050	1.004	**0.995**	1.002
Canada	0.797	0.006	54.2%	0.470	0.660	1.010	0.630	1.013	**1.000**	1.003
Japan	-0.787	0.005	49.4%	0.350	0.030	1.009	0.220	1.012	1.006	1.007
New Zealand	**2.55***	0.026	57.2%	0.120	0.000	**1.002**	0.080	1.017	1.003	1.011
Sweden	0.637	0.002	53.6%	0.540	0.080	1.012	0.510	1.013	1.005	1.004
UK	-0.106	0.000	51.7%	0.920	0.000	1.016	0.970	1.014	1.002	1.005
Switzerland	-0.141	0.000	51.7%	0.810	0.010	1.010	0.760	1.006	1.001	**1.000**
Norway	0.569	0.002	54.5%	0.560	0.260	1.010	0.650	1.014	1.006	1.002
Denmark	-0.014	0.001	51.4%	0.760	0.090	1.016	0.930	1.013	1.003	1.001
Israel	-0.355	0.001	50.9%	0.620	0.000	1.009	0.780	1.004	**0.999**	1.003
Brazil	**3.37***	0.034	55.3%	0.030	0.000	**0.982**	0.070	**0.982**	**0.991**	1.002
South Africa	1.073	0.003	49.8%	0.490	0.020	1.013	0.460	1.023	1.011	1.009
Turkey	1.541	0.003	47.2%	0.390	0.120	1.020	0.400	1.029	1.007	1.010
Russia	-0.055	0.000	51.9%	0.920	0.100	1.006	0.990	1.006	1.003	1.002
South Korea	**1.60****	0.020	58.3%	0.130	0.000	1.001	0.250	1.005	1.005	1.002
Mexico	**1.91***	0.025	49.8%	0.120	0.400	**0.996**	0.095	1.001	**0.998**	1.006
Singapore	0.491	0.008	54.8%	0.120	0.000	**0.998**	0.090	**0.990**	**0.996**	**0.995**
Phillipines	0.355	0.003	51.3%	0.340	0.000	1.006	0.300	1.005	**0.998**	**0.997**
Poland	0.193	0.000	54.1%	0.910	0.040	1.014	0.840	1.014	1.002	1.003
Taiwan	0.237	0.003	50.9%	0.460	0.000	1.010	0.360	1.008	1.003	1.000
Chile	**2.18***	0.028	52.0%	0.100	0.000	1.000	0.180	1.003	1.003	1.003
Hungary	0.580	0.001	52.2%	0.690	0.080	1.010	0.760	1.014	1.002	1.002
Czech	-0.062	0.000	55.5%	0.940	0.030	1.011	0.820	1.009	**0.999**	**0.999**
Colombia	**2.46***	0.038	55.0%	0.010	0.020	**0.990**	0.020	**1.000**	**0.987**	**0.995**
Peru	**0.392****	0.007	55.6%	0.210	1.000	1.001	0.230	1.003	**0.998**	**0.993**
Indonesia	0.010	0.000	50.6%	0.950	0.130	1.008	0.830	1.006	1.004	1.003
Thailand	0.199	0.001	54.2%	0.510	0.000	1.007	0.250	1.005	**0.999**	**0.998**

Table 5 – Results for In-Sample and Out-of-Sample analysis - HY

Table 5 shows the results from the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-Causality test. GC Robust shows the p-value of the Rossi (2005) Granger-Causality test robust to instabilities. Table 5 also shows the result of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stands for, respectively, the 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

Countries	**In-Sample**					**Out-of-Sample**				
	Coeff	**R^2**	**HR**	**GC**	**GC Robust**	**1 Week**	**P-Value CW**	**2 Weeks**	**4 Weeks**	**8 Weeks**
Australia	**2.67***	0.209	59.8%	0.000	0.000	**0.865**	0.000	**0.907**	**0.933**	**0.954**
Canada	**1.74***	0.179	62.7%	0.000	0.000	**0.876**	0.000	**0.896**	**0.933**	**0.962**
Japan	**-1.15***	0.076	54.5%	0.000	0.000	**0.937**	0.000	**0.973**	**0.990**	**0.986**
New Zealand	**2.31***	0.139	58.1%	0.000	0.000	**0.902**	0.000	**0.919**	**0.945**	**0.962**
Sweden	**1.51***	0.082	53.0%	0.000	0.000	**0.933**	0.000	**0.954**	**0.969**	**0.985**
UK	**0.840***	0.039	54.5%	0.000	0.000	**0.969**	0.000	**0.973**	**0.984**	**1.001**
Switzerland	0.017	0.000	51.6%	0.940	0.000	1.009	0.260	1.014	1.007	1.017
Norway	**1.26***	0.058	54.7%	0.000	0.000	**0.946**	0.000	**0.958**	**0.975**	**0.994**
Denmark	**0.495***	0.013	54.8%	0.010	0.000	**0.993**	0.050	**0.998**	**0.995**	1.004
Israel	**0.836***	0.047	58.6%	0.000	0.000	**0.978**	0.010	**0.982**	**0.984**	**0.994**
Brazil	**2.98***	0.172	59.7%	0.000	0.000	**0.864**	0.000	**0.840**	**0.892**	**0.941**
South Africa	**2.32***	0.094	55.2%	0.000	0.000	**0.906**	0.000	**0.926**	**0.952**	**0.959**
Turkey	**2.53***	0.060	57.5%	0.000	0.000	**0.893**	0.000	**0.926**	**0.959**	**0.966**
Russia	**0.843**	0.052	54.4%	0.000	0.000	**0.973**	0.000	**0.986**	**0.995**	1.001
South Korea	**1.96***	0.192	60.6%	0.000	0.000	**0.870**	0.000	**0.896**	**0.927**	**0.958**
Mexico	**2.11***	0.199	59.8%	0.000	0.000	**0.881**	0.000	**0.919**	**0.937**	**0.967**
Singapore	**0.583***	0.069	59.8%	0.000	0.000	**0.944**	0.000	**0.953**	**0.969**	**0.985**
Phillipines	**0.709***	0.078	58.1%	0.000	0.000	**0.939**	0.000	**0.959**	**0.969**	**0.980**
Poland	**1.90***	0.086	56.6%	0.000	0.000	**0.939**	0.000	**0.965**	**0.976**	**0.991**
Taiwan	**0.470***	0.067	60.2%	0.000	0.000	**0.946**	0.000	**0.959**	**0.974**	**0.984**
Chile	**1.96***	0.146	60.5%	0.000	0.000	**0.917**	0.000	**0.948**	**0.950**	**0.962**
Hungary	**1.63***	0.059	56.4%	0.000	0.000	**0.961**	0.000	**0.976**	**0.984**	**0.989**
Czech	**0.789***	0.020	55.5%	0.000	0.000	**0.987**	0.010	**0.994**	**0.993**	**1.000**
Colombia	**1.50***	0.091	62.3%	0.000	0.000	**0.951**	0.000	**0.959**	**0.952**	**0.960**
Peru	**0.418***	0.048	59.7%	0.000	0.000	**0.975**	0.000	**0.984**	**0.986**	**0.990**
Indonesia	**1.07***	0.057	54.7%	0.000	0.000	**0.945**	0.000	**0.955**	**0.956**	**0.979**
Thailand	**0.307***	0.019	56.4%	0.000	0.000	**0.989**	0.000	**0.989**	**0.992**	**0.994**

Table 6 – Results for In-Sample and Out-of-Sample analysis - ML

Table 6 shows the results from the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-Causality test. GC Robust shows the p-value of the Rossi (2005) Granger-Causality test robust to instabilities. Table 6 also shows the result of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stands for, respectively, the 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

	ML									
Countries	In-Sample					Out-of-Sample				
	Coeff	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**-0.033***	0.063	57.2%	0.030	0.000	**0.991**	0.040	**0.947**	**0.925**	**0.944**
Canada	**-0.018***	0.037	55.8%	0.060	0.140	**1.000**	0.015	**0.970**	**0.969**	**0.969**
Japan	**0.009****	0.008	47.5%	0.220	0.880	1.010	0.480	**0.994**	**0.997**	**1.000**
New Zealand	**-0.026***	0.033	55.9%	0.060	0.160	**1.000**	0.090	**0.968**	**0.962**	**0.964**
Sweden	**-0.019***	0.026	53.4%	0.000	0.120	**0.991**	0.080	**0.979**	**0.981**	**0.988**
UK	**-0.016***	0.025	49.7%	0.060	0.300	**0.997**	0.100	**0.976**	**0.979**	**0.982**
Switzerland	**-0.008****	0.005	53.3%	0.110	0.500	1.000	0.210	**0.998**	**0.995**	**0.996**
Norway	**-0.023***	0.037	54.7%	0.000	0.000	**0.977**	0.020	**0.962**	**0.967**	**0.986**
Denmark	**-0.014***	0.019	52.8%	0.020	0.190	**0.994**	0.080	**0.987**	**0.986**	**0.991**
Israel	-0.006	0.005	52.8%	0.320	0.180	1.009	0.610	1.008	1.008	1.001
Brazil	**-0.030***	0.034	55.2%	0.050	0.020	1.003	0.110	**0.945**	**0.936**	**0.970**
South Africa	**-0.031***	0.033	54.2%	0.030	0.000	**0.991**	0.013	**0.949**	**0.942**	**0.956**
Turkey	**-0.029***	0.015	51.3%	0.050	0.000	1.010	0.220	**0.960**	**0.957**	**0.974**
Russia	-0.010	0.013	52.8%	0.070	0.030	1.002	0.390	1.001	1.002	1.005
South Korea	**-0.021***	0.040	55.8%	0.060	0.000	0.996	0.018	**0.956**	**0.953**	**0.962**
Mexico	**-0.021***	0.037	53.4%	0.110	0.010	1.004	0.200	**0.979**	**0.976**	**0.993**
Singapore	**-0.0064***	0.016	54.8%	0.030	0.150	**0.995**	0.050	**0.984**	**0.983**	**0.985**
Phillipines	-0.007	0.014	52.0%	0.000	0.110	**0.997**	0.060	**0.992**	**0.993**	**0.987**
Poland	**-0.022***	0.020	55.9%	0.130	0.080	1.007	0.340	**0.987**	**0.993**	**0.999**
Taiwan	**-0.006***	0.021	54.1%	0.020	0.030	**0.996**	0.050	**0.981**	**0.983**	**0.989**
Chile	**-0.029***	0.060	55.2%	0.000	0.000	**0.984**	0.020	**0.952**	**0.956**	**0.976**
Hungary	**-0.022***	0.021	54.7%	0.070	0.170	**0.999**	0.030	**0.985**	**0.988**	**0.994**
Czech	-0.012	0.009	54.5%	0.160	0.370	1.005	0.290	**0.997**	**0.997**	**1.000**
Colombia	**-0.022***	0.037	54.7%	0.000	0.000	**0.994**	0.040	**0.966**	**0.954**	**0.964**
Peru	**-0.005****	0.011	55.0%	0.070	0.440	1.003	0.180	**0.999**	1.003	1.010
Indonesia	**-0.021***	0.042	51.1%	0.000	0.040	**0.980**	0.020	**0.965**	**0.971**	**0.974**
Thailand	**-0.007***	0.017	56.3%	0.000	0.000	**0.994**	0.010	**0.989**	**0.989**	**0.990**

Table 7 – Results for In-Sample and Out-of-Sample analysis - MLE

Table 7 shows the results from the in-sample and out-of-sample exercises. Coeff and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR is the market timing test, indicating the percentage of times that the estimated model correctly predicts the realized change in the exchange rate. GC is the p-value of the traditional Granger-Causality test. GC Robust shows the p-value of the Rossi (2005) Granger-Causality test robust to instabilities. Table 7 also shows the result of the out-of-sample exercises for different forecasting horizons. The ratio between the root mean square prediction error of a model and that given by the random walk without a drift is shown in the table. P-value represents the result of the Clark and West (2006) test statistic. *, ** stands for, respectively, the 5% and 10% levels of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

	MLE									
Countries	**In-Sample**					**Out-of-Sample**				
	Coeff	**R^2**	**HR**	**GC**	**GC Robust**	**1 Week**	**P-Value CW**	**2 Weeks**	**4 Weeks**	**8 Weeks**
Australia	**-0.019***	0.059	57.2%	0.000	0.020	**0.989**	0.000	**0.946**	**0.939**	**0.950**
Canada	**-0.011***	0.037	57.0%	0.010	0.300	**0.988**	0.030	**0.965**	**0.960**	**0.960**
Japan	0.002	0.001	47.8%	0.600	1.000	1.008	0.870	1.003	1.003	1.002
New Zealand	**-0.016***	0.037	55.6%	0.000	0.090	**0.987**	0.000	**0.965**	**0.964**	**0.965**
Sweden	**-0.012***	0.030	55.2%	0.000	0.050	**0.984**	0.010	**0.971**	**0.973**	**0.977**
UK	**-0.009***	0.022	52.0%	0.020	0.200	**0.992**	0.030	**0.978**	**0.979**	**0.987**
Switzerland	**-0.006***	0.008	53.1%	0.030	0.160	**0.993**	0.010	**0.990**	**0.990**	**0.992**
Norway	**-0.013***	0.035	54.1%	0.000	0.000	**0.973**	0.000	**0.955**	**0.958**	**0.969**
Denmark	**-0.008***	0.020	51.9%	0.000	0.070	**0.985**	0.000	**0.978**	**0.979**	**0.983**
Israel	-0.004	0.007	52.7%	0.110	0.310	1.001	0.240	**0.999**	**0.997**	**0.998**
Brazil	**-0.018***	0.034	55.2%	0.000	0.120	**0.990**	0.020	**0.952**	**0.952**	**0.967**
South Africa	**-0.015***	0.020	52.7%	0.030	0.310	**0.991**	0.090	**0.968**	**0.964**	**0.970**
Turkey	**-0.021***	0.023	54.8%	0.000	0.000	**0.994**	0.090	**0.950**	**0.947**	**0.961**
Russia	**-0.009***	0.036	50.8%	0.000	0.000	**0.984**	0.000	**0.978**	**0.982**	**0.989**
South Korea	**-0.014***	0.054	56.3%	0.000	0.020	**0.976**	0.020	**0.956**	**0.959**	**0.966**
Mexico	**-0.013***	0.039	52.5%	0.030	0.030	**0.990**	0.030	**0.973**	**0.975**	**0.986**
Singapore	**-0.004***	0.021	55.6%	0.000	0.080	**0.984**	0.000	**0.975**	**0.976**	**0.979**
Phillipines	**-0.004***	0.013	53.1%	0.010	0.240	**0.995**	0.030	**0.990**	**0.991**	**0.996**
Poland	**-0.016***	0.033	55.2%	0.010	0.030	**0.988**	0.010	**0.973**	**0.976**	**0.986**
Taiwan	**-0.004***	0.033	56.3%	0.000	0.000	**0.981**	0.000	**0.968**	**0.973**	**0.980**
Chile	**-0.015***	0.049	54.5%	0.000	0.000	**0.985**	0.010	**0.961**	**0.962**	**0.972**
Hungary	**-0.014***	0.024	52.7%	0.010	0.070	**0.990**	0.020	**0.978**	**0.979**	**0.984**
Czech	**-0.009***	0.013	54.2%	0.030	0.170	**0.995**	0.020	**0.988**	**0.987**	**0.991**
Colombia	**-0.012***	0.032	52.2%	0.000	0.060	**0.990**	0.020	**0.970**	**0.966**	**0.973**
Peru	**-0.003***	0.011	55.9%	0.030	0.140	**0.994**	0.020	**0.989**	**0.987**	**0.989**
Indonesia	**-0.012***	0.040	53.8%	0.000	0.040	**0.957**	0.000	**0.943**	**0.955**	**0.966**
Thailand	**-0.005***	0.023	54.5%	0.000	0.000	**0.986**	0.000	**0.976**	**0.977**	**0.980**

Figure 1 – Results of the Giacomini-Rossi (2010) fluctuation test for T10Y

Figure 1 shows the results of the Giacomini and Rossi (2010) for the stability of the relative performance of the model (T10Y) with respect to the benchmark. The test statistics (solid lines) and critical value (dotted lines) are shown for all countries in the sample.

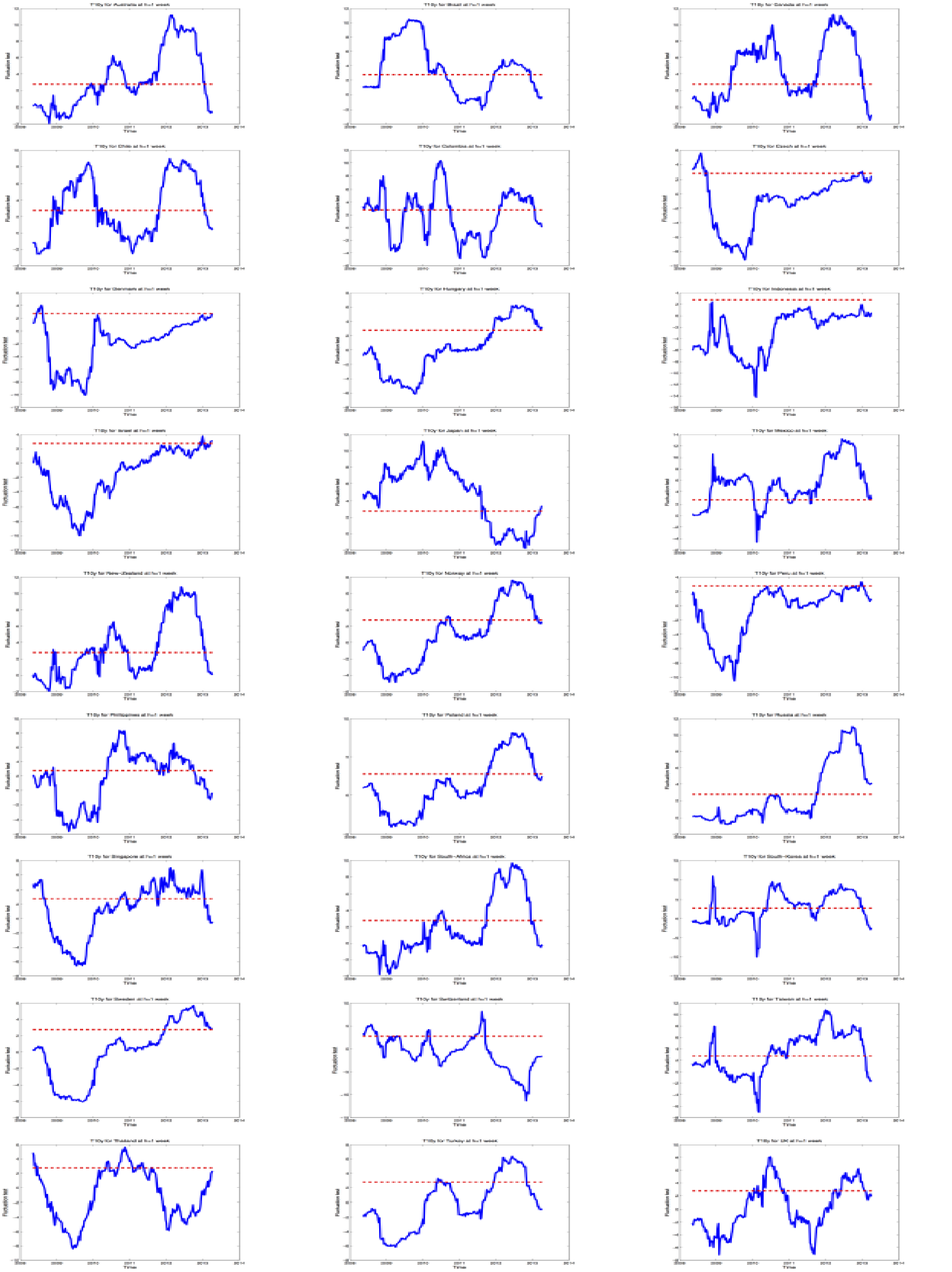

Figure 2 – Results of the Inoue and Rossi (2012) test for T10Y

Figure 2 shows the results of the Inoue and Rossi (2012) for the robustness of the choice of the window size. Results are reported for all countries in the sample.

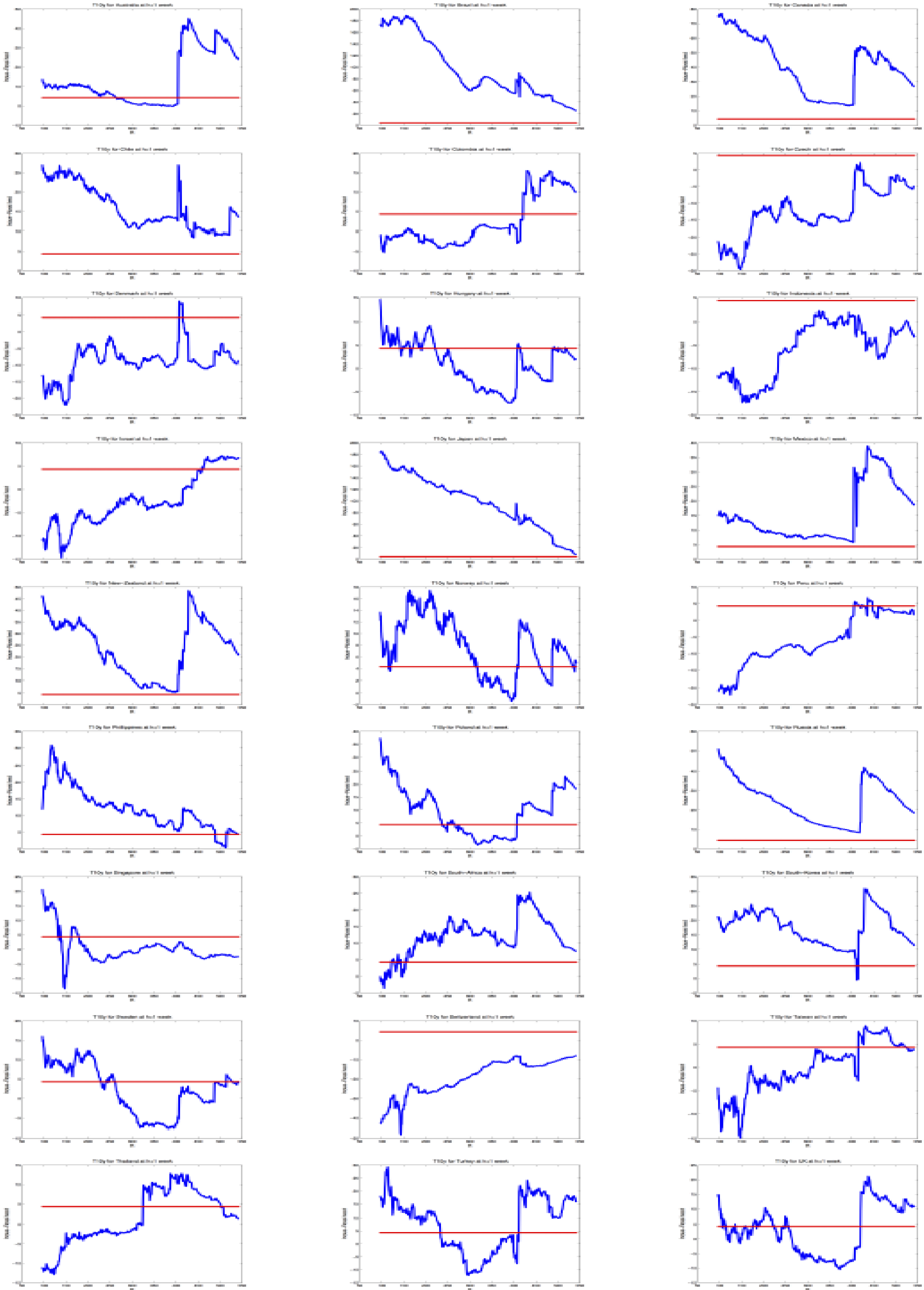

Figure 3 – Results of the Giacomini-Rossi (2010) fluctuation test for VIX

Figure 3 shows the results of the Giacomini and Rossi (2010) for the stability of the relative performance of the model (VIX) with respect to the benchmark. The test statistics (solid lines) and critical value (dotted lines) are shown for all countries in the sample.

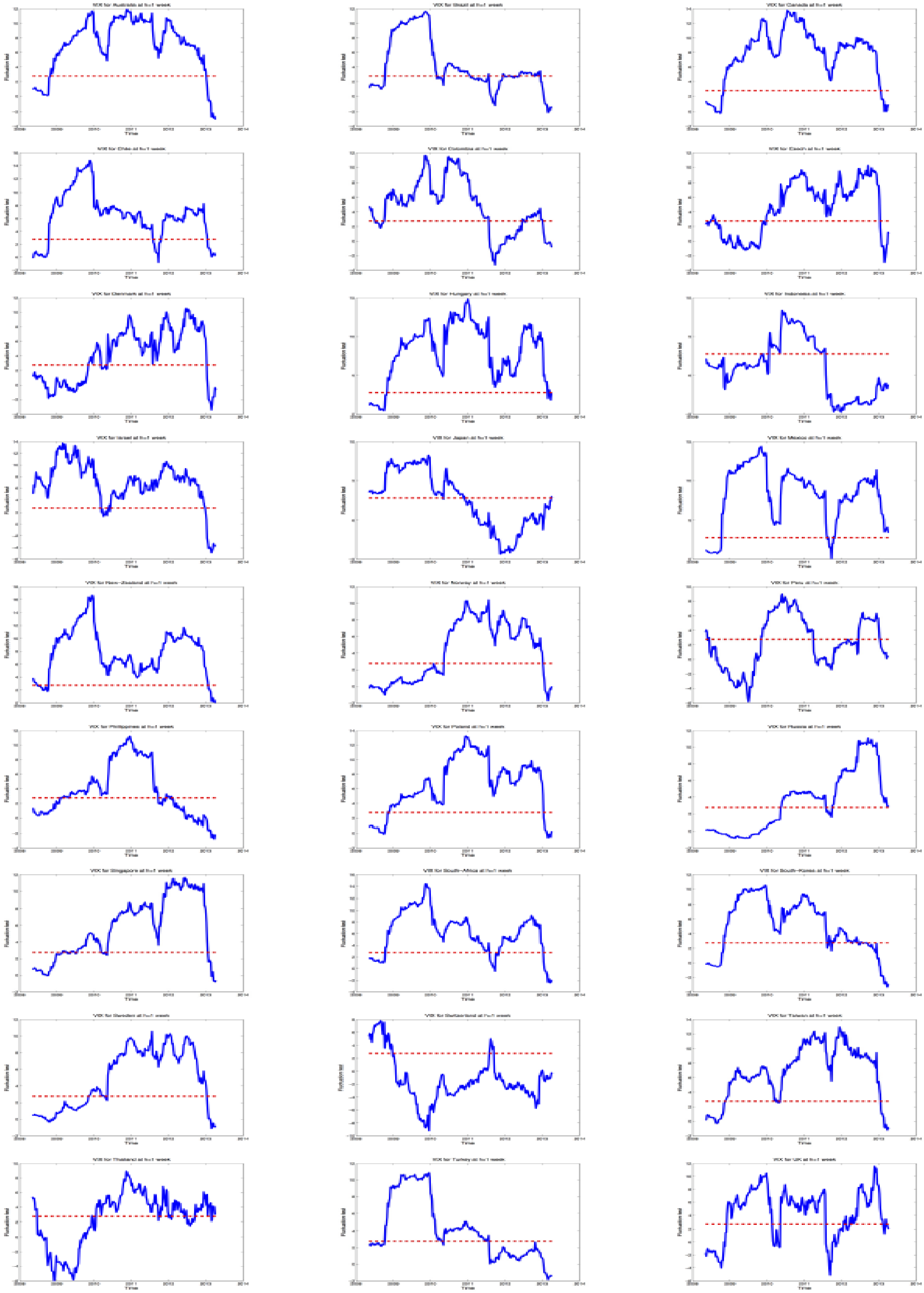

Figure 4 – Results of the Inoue and Rossi (2012) test for VIX

Figure 4 shows the results of the Inoue and Rossi (2012) for the robustness of the choice of the window size. Results are reported for all countries in the sample.

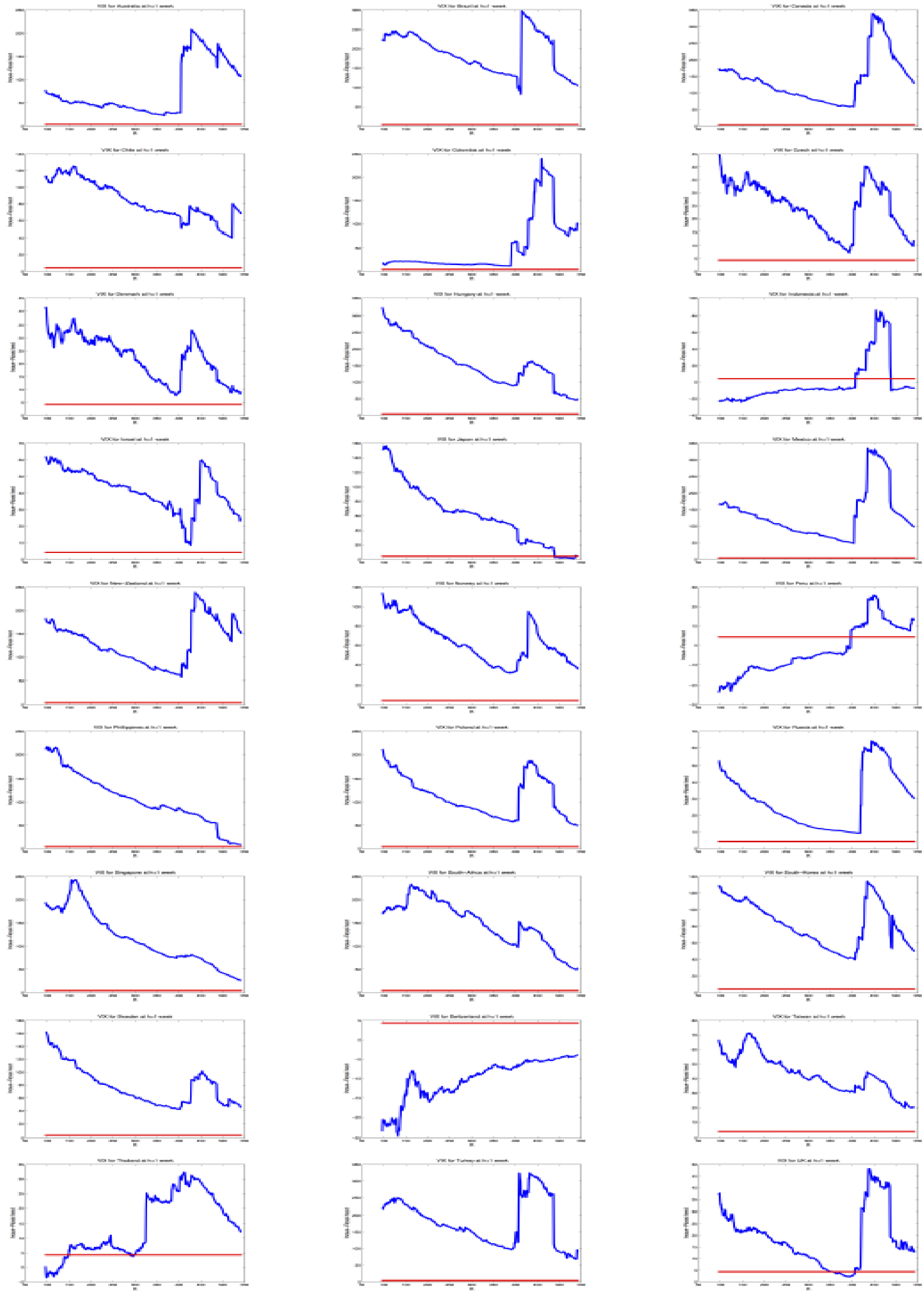

Figure 5 – Results of the Giacomini-Rossi (2010) fluctuation test for TED

Figure 5 shows the results of the Giacomini and Rossi (2010) for the stability of the relative performance of the model (TED) with respect to the benchmark. The test statistics (solid lines) and critical value (dotted lines) are shown for all countries in the sample.

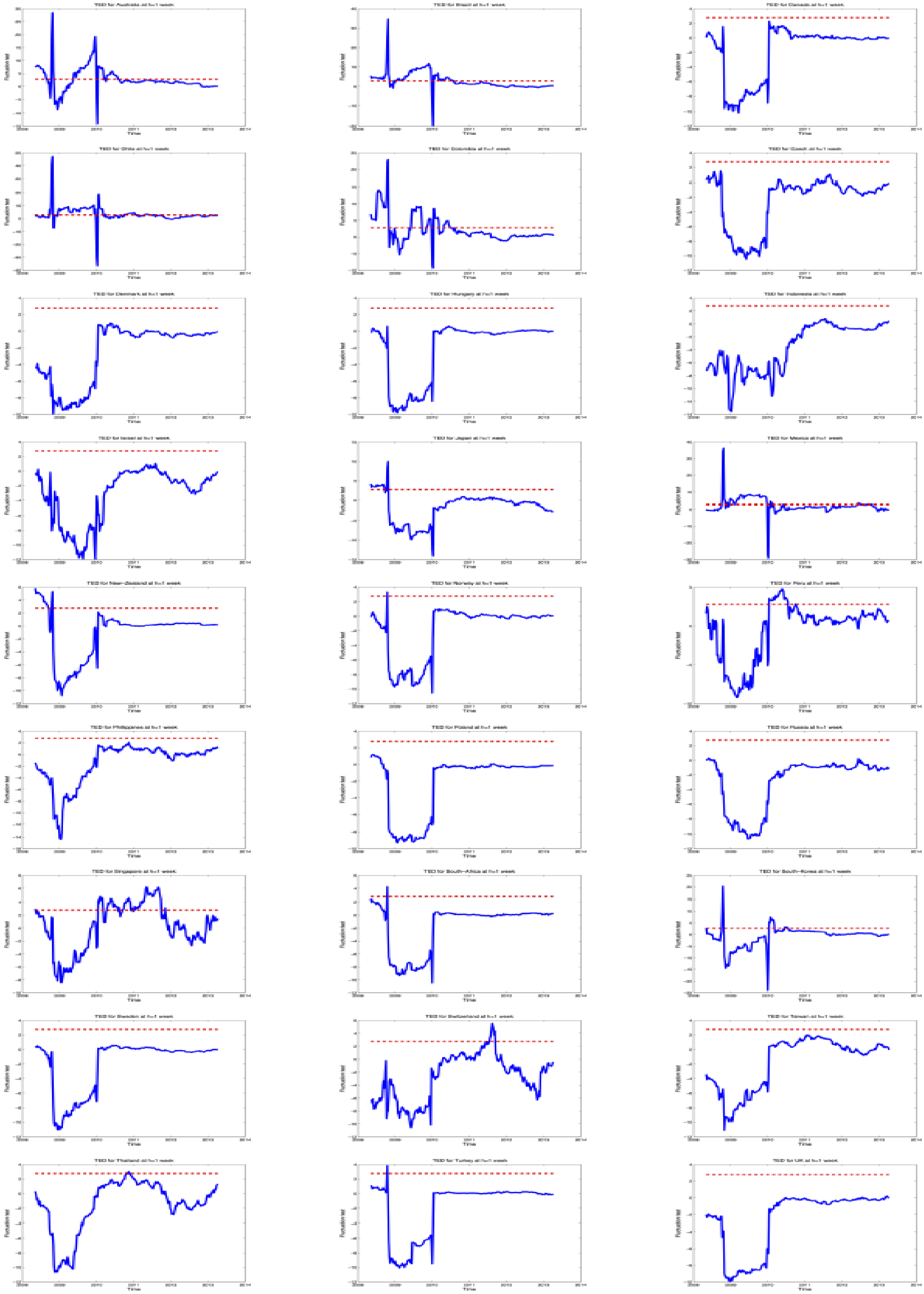

Figure 6 – Results of the Inoue and Rossi (2012) test for TED

Figure 6 shows the results of the Inoue and Rossi (2012) for the robustness of the choice of the window size. Results are reported for all countries in the sample.

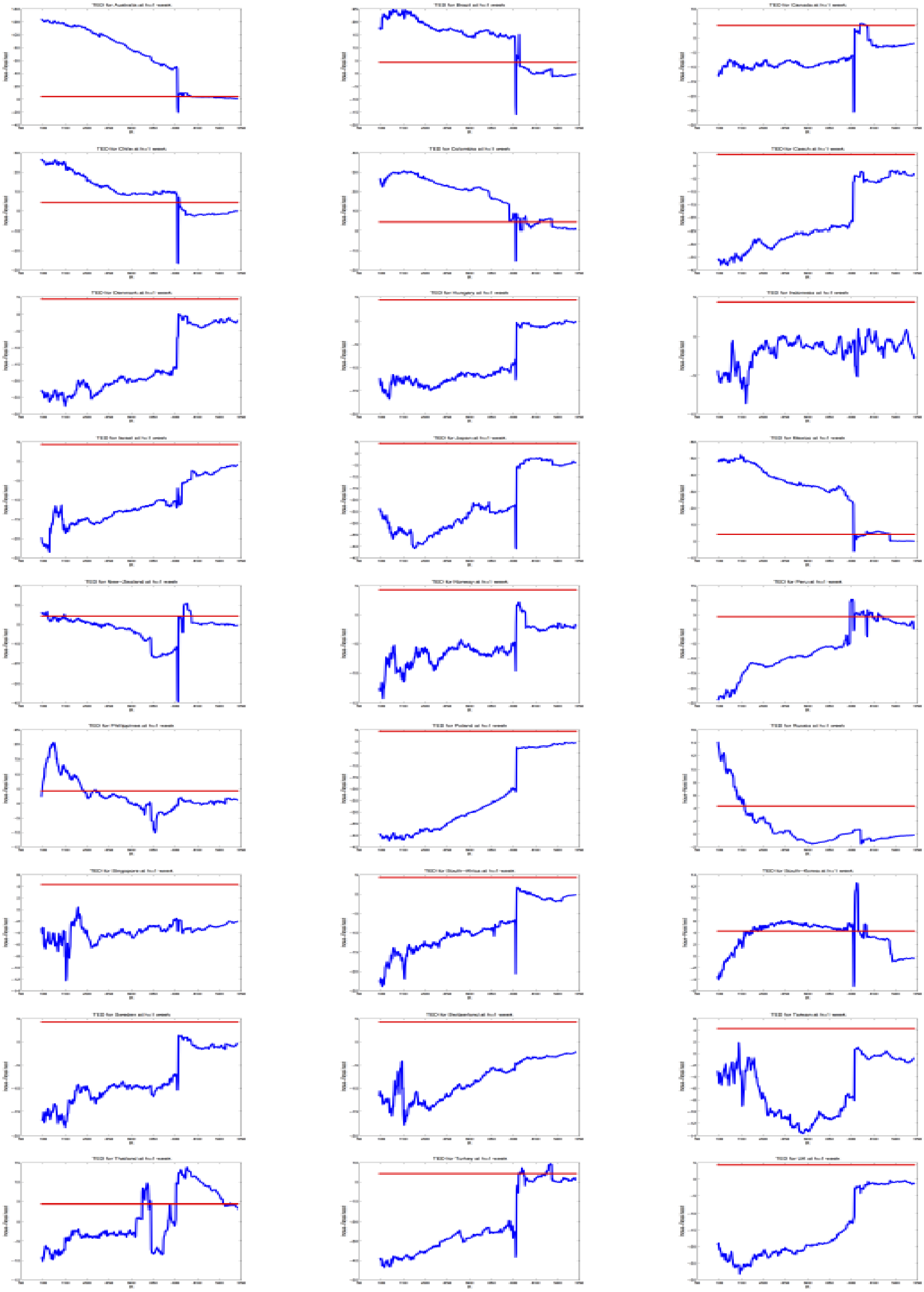

Figure 7 – Results of the Giacomini-Rossi (2010) fluctuation test for HY

Figure 7 shows the results of the Giacomini and Rossi (2010) for the stability of the relative performance of the model (HY) with respect to the benchmark. The test statistics (solid lines) and critical value (dotted lines) are shown for all countries in the sample.

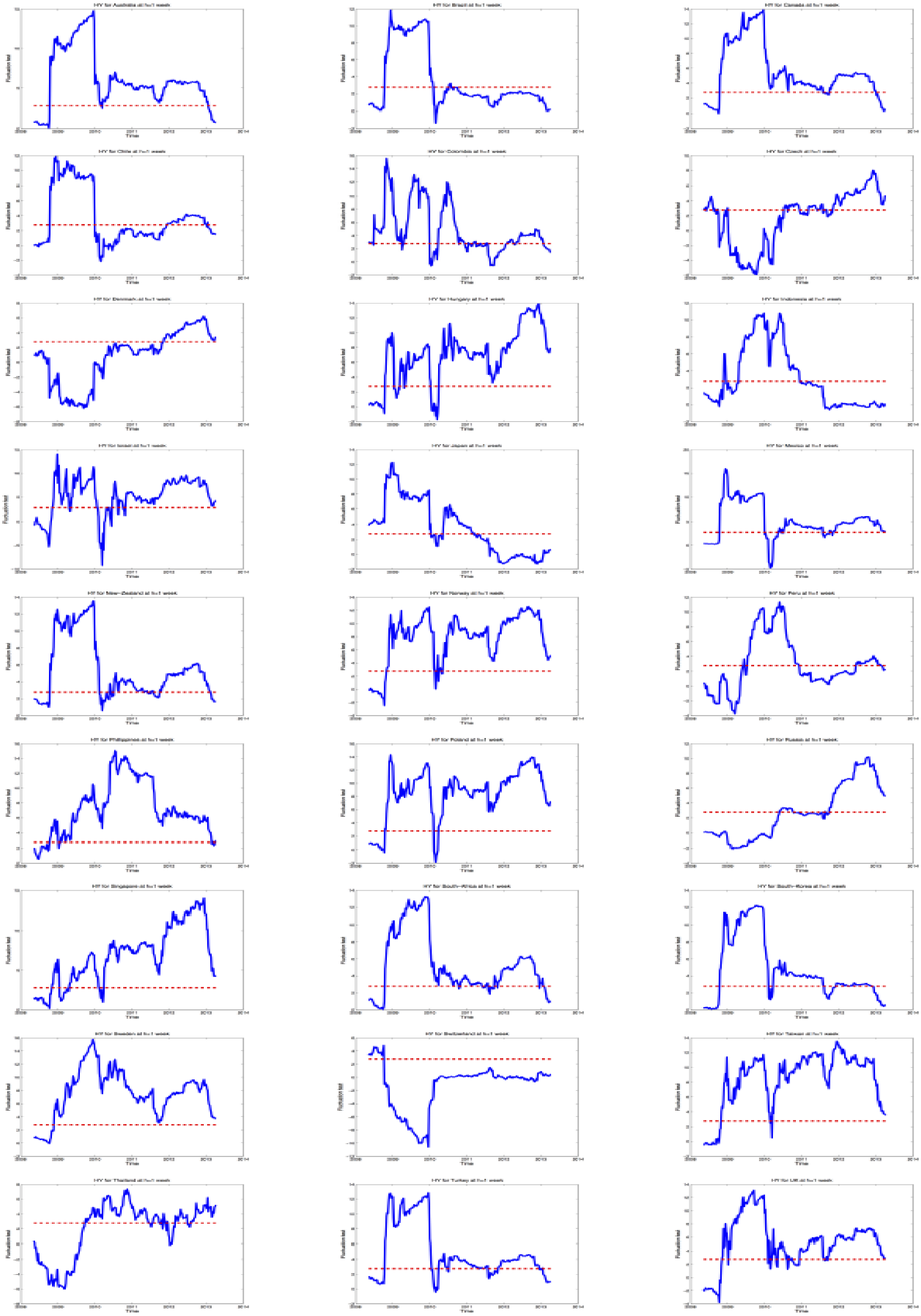

Figure 8 – Results of the Inoue and Rossi (2012) test for HY

Figure 8 shows the results of the Inoue and Rossi (2012) for the robustness of the choice of the window size. Results are reported for all countries in the sample.

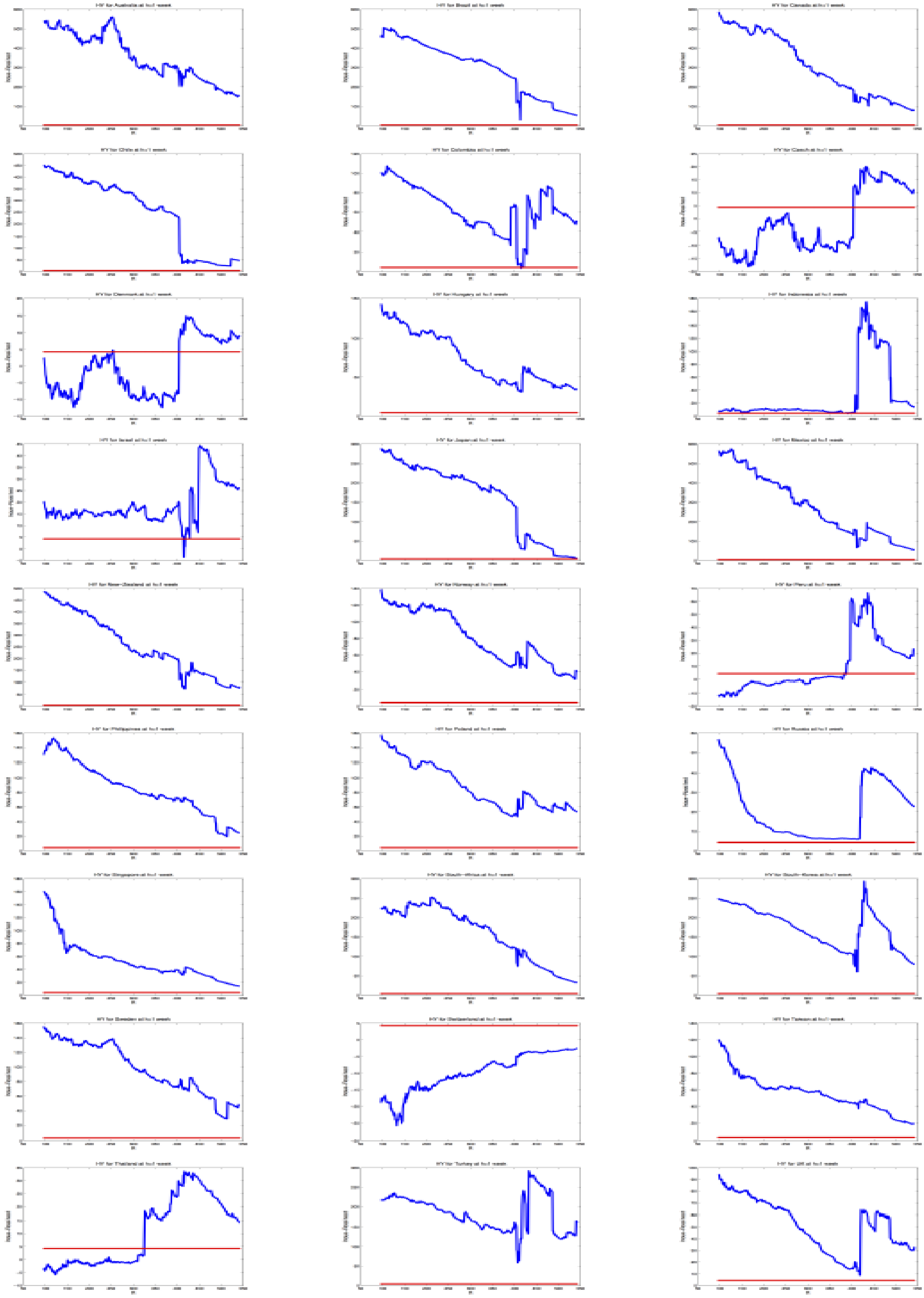

Figure 9 – Results of the Giacomini-Rossi (2010) fluctuation test for MLE

Figure 9 shows the results of the Giacomini and Rossi (2010) for the stability of the relative performance of the model (MLE) with respect to the benchmark. The test statistics (solid lines) and critical value (dotted lines) are shown for all countries in the sample.

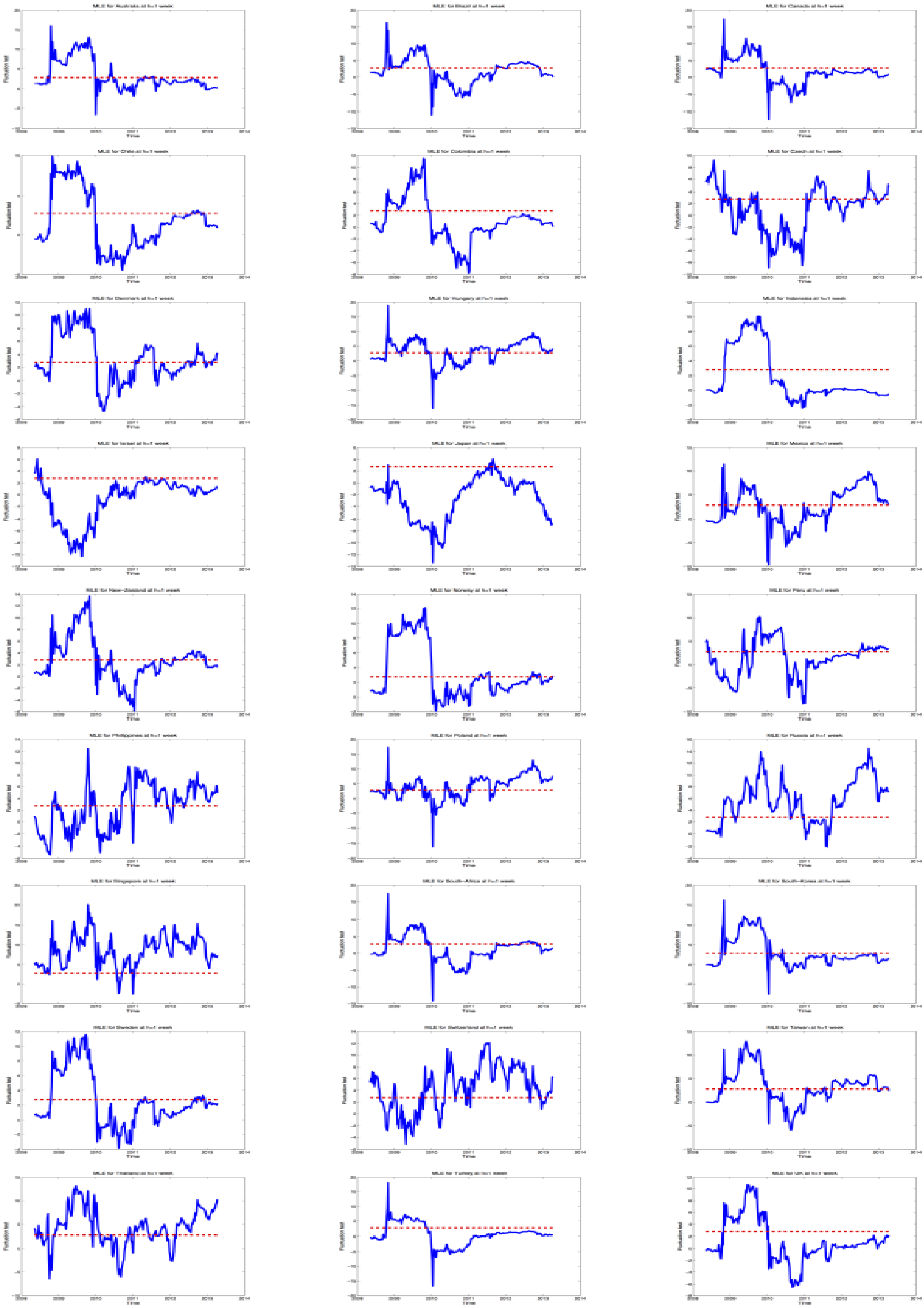

Figure 10 – Results of the Inoue and Rossi (2012) test for MLE

Figure 10 shows the results of the Inoue and Rossi (2012) for the robustness of the choice of the window size. Results are reported for all countries in the sample.