LIQUIDITY and EXCHANGE RATES

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ABSTRACT

This paper studies the predictive power of several proxies for liquidity in forecasting exchange rates for a set of countries from January 2001 to April 2013. The results indicate that changes in funding liquidity of U.S. financial intermediaries impact exchange rates around the globe; however, the type of funding and its relevance in explaining exchange rate movements vary across time. Public liquidity represented by U.S. monetary aggregates is not robustly significant in forecasting exchange rate changes across time, countries or forecasting horizons. By contrast, the long-term interest rate and risk taking indicators have robust in-sample and out-of-sample predictive power with respect to exchange rates. Finally, the paper confirms that dynamic factors extracted from a panel of several liquidity indicators are useful in predicting exchange rate movements.

Keywords: Exchange rates; Liquidity; Forecasting.

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1. INTRODUCTION

Following the 2007-2008 financial crisis, liquidity was placed at the center of debate with respect to the causes, consequences and management of the crisis, becoming perhaps the dominant topic of speeches of governors of central banks around the world over the last several years.[2] According the Committee on the Global Financial System - CGFS (2011), the key role of liquidity in the public debate reflects its importance for global financial stability either in amplifying countries' vulnerabilities or in the aftermath of the burst of these financial imbalances.

Government officials have taken particular interest in the impact of liquidity changes on the dynamics of the exchange rate. On one side, many policy makers, mainly in emerging markets, blamed recent unconventional monetary policies in advanced economies for exchange rate movements. Terms such as "monetary tsunami" and "currency wars" were used to refer to the increase in liquidity generated by monetary policy in advanced economies.[3] On the other side, officials and central bankers in advanced economies argue that private liquidity – liquidity created by banks and other financial institutions – in addition to improving growth prospects in emerging economies, is a more important driver of exchange rates than advanced economy monetary policies. Although the debate on the topic has been intense, studies of the impact of changes in liquidity on the dynamics of exchange rates remain scarce.[4]

This paper sheds light on this discussion by analyzing the role of liquidity 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, using several commonly used proxies for liquidity to examine their predictive power with respect to the trajectory of exchange rates in these countries. In addition to traditional forecasting exercises, more robust tests that address possible instability in the relationship between liquidity and the exchange rate are conducted.

The paper shows that changes in private funding liquidity can predict exchange rate movements. However, the paper shows that the types of funding liquidity relevant to forecasting the dynamics of exchange rates vary in importance over time. The results show

[2] In an internet search of the term "global liquidity," one finds on the first page speeches on the topic by FED, ECB, BIS, Bank of France and Bank of Canada board members.

[3] "This crisis started in the developed world. It will not be overcome … through … quantitative easing policies that have triggered … a monetary tsunami, have led to a currency war and have introduced new and perverse forms of protectionism in the world" - Brazilian President Dilma Roussef (2012), in a speech.

[4] One exception is Adrian et al. (2010) who analyzes the effect of funding liquidity on the dynamics of the exchange rate.

that funding liquidity represented by total outstanding overnight repurchase agreements (REPO) of US financial intermediaries can predict exchange rate changes in the period between 2008 and 2010. However, funding liquidity represented by total loans of financial institutions from other financial intermediaries can predict exchange rate movements in the subsequent period from 2010 to 2012. This paper indicates that none of the other sources of funding liquidity are relevant in predicting exchange rate movements.

Terms such as "monetary tsunami" and "currency wars" were used to describe the impact of the unconventional monetary policy adopted the Fed after the 2007-2008 financial crisis on foreign exchange markets. The results of the present paper provide little support for the use of these terms. The paper shows that monetary (public) liquidity represented by U.S. monetary aggregates does not robustly and significantly impact exchange rates over time, forecast horizons or countries. The study finds that the predictive power of the monetary aggregates is restricted to brief periods of time and to a small set of countries.

A different story can be told with respect to long-term interest rates and risk-taking indicators. The paper shows that these measures usually related to movements in global liquidity 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 and the high-yield spread variables generally used to measure investors' risk appetite 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 variables is more stable over time than that of the funding liquidity or monetary aggregates. Finally, the paper confirms that common movements extracted from several liquidity indicators consistently forecast exchange rates.

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 liquidity proxies 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 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 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[5], 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 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.

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.[6] Focusing on the relationship between liquidity and macroeconomic fundamentals, Glocker and Towbin (2012), applying a structural VAR to Brazil, 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

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

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

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.[7] 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.[8]

Bachetta and Wincoop (2004, 2011) developed the scapegoat theory, which is consistent with this role of unobservable variables in explaining movements of exchange rates. The theory asserts that if the dynamics of exchange rates are partially determined by unobservable variables, changes in agents' expectations with respect to the structural parameters of the economy generated by shocks to these unobservable variables will generate instability in the relationship between exchange rates and fundamentals.

Evans and Lyons (2002, 2005, 2008) and Chinn and Moore (2010), seeking to address this question, adopt a microstructure approach to traditional macroeconomic models. In these papers, the inclusion of order flow variables would solve the problem of the conventional

[7] 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.

[8] 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.

models, as these variables would account for shocks that lead to instability in the relationship between exchange rates and fundamentals.[9]

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 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.

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 data are collected from DataStream.

3.1 LIQUIDITY MEASURES

The literature adopts different definitions of, and employs several proxies for, liquidity. As discussed in the CGFS (2011), it is unlikely that a single measure can capture all relevant aspects of global liquidity. Therefore, in assessing the role of liquidity, it is important to rely on a variety of measures, where the selection of any particular combination depends on the specific analytical question under consideration.[10] In this paper, we employ several proxies used in the literature to analyze the predictive power of liquidity with respect

[9] One possibility discussed in the microstructure approach literature is that order flow variables carry private information that becomes embedded in the exchange rate.
[10] See Domanski et al. (2011) for a discussion of liquidity measures.

to the exchange rate. Following Chen et al. (2012), we focus on both price and quantity variables to obtain a more accurate view of the impact of liquidity on exchange rates.[11]

It is important to note that we do not attempt to find a best proxy for liquidity, as it is very difficult to disentangle one proxy from another. The paper attempts to determine which proxy is most useful in forecasting the exchange rate and thereby shed light on the mechanism through which liquidity impacts exchange rate dynamics.

Funding Liquidity: Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011) place the relationship between funding and market liquidity at the center of debate over liquidity spirals. Empirically, Adrian et al. (2010) find that funding liquidity, as proxied by the total outstanding stock of commercial paper (COMMERCIAL) and total outstanding overnight repurchase agreements (REPO) of U.S. financial intermediaries, has predictive power with respect to the dynamics of the exchange rates of several countries in relation to the U.S. dollar. We add these two variables as sources of funding for the banking sector.

Chen et al. (2012) define core liabilities as the funds that banks draw on in normal times. The authors argue that households supply liquidity to commercial banks through deposits. To analyze the role of core liabilities, we use total resident deposits in banks as our quantity measure of core liabilities of the banking sector (DEPOSITS). Following the authors, we use the spread between the domestic deposit rate for deposits with maturities of up to one year and the 6-month interbank interest rate as the cost of deposit funding (SPREAD).

Financial institutions can also supply liquidity by funding other institutions. Chen et al. (2012) define such funding as noncore liabilities. Following the authors, we use total loans and securities of financial institutions from other financial intermediaries as our proxy for noncore liabilities (BORROWINGS).

Credit Aggregates: The CGFS (2011) states that credit aggregates are one of the main indicators of global liquidity. Domanski et al. (2011) argue that credit indicators represent the final interaction between different sources of liquidity. Chen et al. (2012) argue that the dynamics of credit provided to the private sector are useful in analyzing the expansion of liquidity from an asset perspective.[12] An extensive literature places the expansion of credit at

[11] One issue is that the paper does not use specific foreign exchange market proxies for liquidity. In our defense, Mancini et al. (2013) show a strong commonality in liquidity across currencies and with equity and bond markets. Unfortunately, data for our full set of countries are not available to construct proxies similar to those used by the authors.
[12] Borio, McCauley and McGuire (2011).

the center of the discussion of the occurrence of financial crises.[13] We therefore use total bank credit to the non-financial private sector as a proxy for liquidity (CREDIT).[14]

Monetary Liquidity: The CGFS (2011) distinguishes two types of liquidity: official liquidity, which is created by the public sector, and private liquidity, which is created by banks and other financial institutions. Several papers use monetary aggregates as proxies for global liquidity.[15] We therefore use broad monetary aggregates such as M0, M1 and M2 as proxies for monetary liquidity. In addition to monetary aggregates, the literature identifies long-term interest rates as proxies for liquidity related to expected future monetary conditions. We add the 10-year treasury yield as our proxy for long-term interest rates (T10Y).[16]

Risk Taking and Uncertainty: Several papers relate private liquidity to variations in risk or uncertainty. Bruno and Shin (2012), for example, find that risk can be an important determinant of private liquidity. 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. We use these variables together with the high yield spread (HY) as our proxies for risk taking and uncertainty.

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 a market based index, the Merrill-Lynch Global and Emerging Markets liquidity index, to verify whether the dynamics

[13] See Gerdesmeier et al. (2010) for a review of this subject.

[14] As discussed by Domanski et al. (2011), the use of credit aggregates as proxies for liquidity may be problematic, as credit might represent an outcome of liquidity and can expand independently of changes in liquidity.

[15] Rueffer and Stracca (2006), D'agostino and Surico (2009), Giese and Tuxen (2007), Darius and Radde (2010) are among the papers that use monetary aggregates as proxies for global liquidity.

[16] 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. As 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, we are not required to address problems associated with aggregating the various measures over different countries, which is not an easy task.

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 liquidity proxies used in this paper. The results in table 1 show that, with the exception of the risk taking proxies and the ML-MLE indexes, correlations among the variables are not very high. Focusing on funding measures, table 1 reports that, although positive, the correlation between the two main funding liquidity measures – REPO and COMMERCIAL – is very low, indicating different uses of these two types of funding. It is interesting to note a negative correlation between deposits and REPO and COMMERCIAL, indicating that the different funding liquidity indicators are substitutable for one another. Total Borrowings from banks from other financial institutions has a low correlation with all other liquidity measures. Table 1 also shows that total credit to the nonfinancial sector is significantly correlated with the volatility measures.

The results in table 1 indicate that correlations among monetary liquidity measures, except that between monetary aggregates and the 10-year Treasury bond yield, are high. In addition, table 1 reports that all volatility and uncertainty measures are highly correlated with each other. Finally, table 1 shows that the common dynamic liquidity indexes are highly correlated with each other and with the volatility proxies.

4. EXCHANGE RATE MODEL AND METHODOLOGY

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

$$\Delta S_{i,t+h} = \alpha_i + \beta_i . \text{Liquidity}_t + u_{i,t+h} \quad (1)$$

Where $\Delta S_{i,t+h}$ represents changes in the (log-) nominal exchange rate for country i, Liquidity_t is one of the liquidity proxies adopted in the text and h is the h-periods ahead forecast that we are interested in.[17]

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 liquidity indicators.

First, note that following Rossi's (2013) notation, we use a single-equation, lagged fundamental model. Therefore, lagged liquidity measures are used to forecast the exchange rate. Because the use of contemporaneous rather than lagged forecasted fundamentals is not a truly out-of-sample exercise (as it uses information not available to the forecaster at time t, making this strategy of limited use), we choose the lagged fundamental model as our baseline specification. Moreover, Rossi (2013) concludes that the choice of a lagged or contemporaneous specification does not significantly affect the final result.

Another possibility noted by Rossi (2013) is the use of Error Correction models. As 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). 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 liquidity measures.[18]

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 liquidity, as we expect that liquidity plays different roles in different countries, a possibility we will investigate.

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, as short-term predictability is the Achilles' heel of forecasting the

[17] Table A.1 in the appendix indicates the ways in which different variables are used in conducting the tests.
[18] 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.

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 LIQUIDITY 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 liquidity 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 liquidity proxies. The estimated coefficients together with the R^2 statistic of the regression are used to analyze the predictive power of the different liquidity 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 the percentage of correct estimations by the model of realized changes in the exchange rate. Several authors (Chen, Rogoff, 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 liquidity 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.[19]

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 is lower observation 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 judge 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 a 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 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 conserve space.

[19] 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 liquidity measures. If liquidity has any predictive power with respect to exchange rate movements, one should fail to reject the hypothesis that the liquidity proxies Granger cause exchange rate movements.

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. [20]

5. RESULTS

Table 2a shows the results for the two funding liquidity proxies: REPO and COMMERCIAL. The results in table 2a indicate that total outstanding overnight repurchase agreements (REPO) of U.S. financial intermediaries exhibit satisfactory predictive power with respect to the exchange rate. These results are in line with those of Adrian et al. (2010).

[20] 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.

Based on the in-sample analysis, the REPO proxy is found to be statistically significant for 14 of the 27 countries in the sample, although the R^2 value is very low. The market timing test produces a result slightly better than a random walk, with the model correctly predicting the direction of changes in the exchange rate 53.1% of the time. The Granger-causality test rejects the hypothesis that the REPO does not Granger cause the exchange rate for 16 countries (at the 10% level of significance). However, the results in table 2a show some signs of instability in the relationship between funding liquidity and the exchange rate. The Granger-causality test that is robust to instabilities rejects the null hypothesis of non-Granger causality for a smaller number of countries.

The out-of-sample analysis shows that the predictive power of the REPO proxy varies with the forecasting horizon. The proxy beats the benchmark random walk model without drift for 13 countries over a one-week forecasting horizon. Once we move to longer forecasting periods, we observe an increase in the number of countries for which the funding liquidity proxy forecast of the exchange rate is superior to the random walk model. For h=8 weeks, for example, the REPO is superior to the random walk for 18 of the 27 countries in the sample.

The fluctuation test yields interesting results, depicted in figure 1a.[21] The test confirms the instability of the relationship between REPO and the exchange rate, with the funding liquidity proxy unable to consistently beat the random walk. The proxy has superior performance to the benchmark especially in the period between 2008 and 2010. After 2010, however, the proxy beats the random walk for only a small number of the countries in the sample. The results in figure 1b indicate that the previous results are robust to the choice of window size and that for a very large interval of window size, the results are unchanged. Finally, the results in table 2a indicate that the total outstanding stock of commercial paper (COMMERCIAL) has no predictive power with respect to the exchange rate in our sample.[22]

Table 2b shows the results for total resident deposits in the banking sector (DEPOSITS) and the spread between the domestic rate for deposits with a maturity of up to one year and the 6-month interbank interest rate (SPREAD). The results indicate a very weak (if any) relationship between this type of funding liquidity and the exchange rate. Based on the in-sample exercises, the Deposits proxy is not statistically significant for any countries in

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

[22] Throughout the text of this paper, we only present results that contain useful information and that are mentioned in the text, as otherwise we would have to show an enormous number of tables and figures. All results are available upon request.

the sample, while the spread indicator is significant for only three countries. The result is even worse when we consider the Granger-causality test. Non-Granger causality between the two proxies and the exchange rate appears to be rejected for only one country and for only two countries if we focus only on the spread indicator, a very poor result.

The results do not improve substantially when we consider the out-of-sample exercises shown in table 2b. The proxies do not outperform the random walk model in one-week ahead forecasting for more than 2 countries in the sample. There is a small improvement when we move to longer-term time horizons, but neither the deposit proxy nor spread proxy outperform the random walk for more than 6 countries in the sample, indicating a very weak (if any) relationship between this type of liquidity and the exchange rate.

Table 2c shows the relationship between total loans and securities of financial institutions from other financial intermediaries (BORROWINGS) and the total banking credit to the non-financial private sector (CREDIT). The results in table 2c indicate a relationship between the Borrowings proxy and the exchange rate. Based on the in-sample exercise, the coefficient of the liquidity proxy is statistically significant at the 10% level of significance for 10 countries, similarly to the REPO proxy, but with a low value for the R^2 statistic. The HR market timing test is also not very promising; the proxy correctly predicts changes in the exchange rate approximately 52% of the time, on average, over all countries. The Granger-causality test rejects non-Granger causality for 9 countries in the sample. Again, the Granger-causality test that is robust to instabilities suggests that the relationship between the two variables is unstable. The test indicates a relation of precedence between the variables for only two countries.

The out-of-sample tests indicate that, for short-periods ahead (h=1), the BORROWINGS proxy beats the benchmark for only one country, while for longer periods, this liquidity proxy outperforms the random walk model. For h=8 weeks, the model beats the benchmark for 17 countries. Interesting patterns are revealed through analysis of the fluctuation test, presented in figure 1c. Similarly to the REPO proxy, the test indicates that the relationship is unstable, but in contrast to the REPO proxy, the instability test shows that the BORROWINGS variable outperforms the benchmark between 2010 and 2012. This finding may indicate that the financial sector changed its source of funding during this period.

Although the literature has extensively documented the role of the credit in asset pricing, the results in table 2c suggest a weak relationship between the CREDIT proxy and the exchange rate. The in-sample exercises do not show any sign of predictability, and the out-of-sample exercise suggests that the credit proxy beats the random walk for only 6 countries at most.

Departing from funding and credit liquidity proxies, tables 2d and 2e show the analysis for our monetary proxies of liquidity. The results in tables 2d and 2e indicate that, although the monetary aggregates have some predictive power with respect to the exchange rate, this power is weak and unstable. Among the monetary aggregates (M0, M1 and M2), the currency component (M0) outperforms its counterparts. The in-sample test shows that M0 has a statistically significant relationship with the exchange rate for 10 countries of the 27 countries in the sample. The HR test shows that, on average, the indicator correctly predicts exchange rate changes 52.3% of the time. In addition, the Granger-causality test rejects the null hypothesis for a similar number of countries (10). The Granger-causality test that is robust to instabilities indicates an unstable relationship between the variable and the exchange rate, rejecting the null for only three countries in the sample.

The out-of-sample results presented in table 2d show that, for a forecasting period of one-week ahead, M0 outperforms the random walk in forecasting the exchange rate for only 4 countries. However, the results improve for longer periods, with M0 beating the random walk model for 13 countries for a forecasting period of 8 weeks ahead. The Giacomini and Rossi (2010) instability test provides insight into the relationship between monetary aggregates and the exchange rate. Figure 1d shows that the model with the monetary aggregate (M0) outperforms the random walk model for only some periods. For most countries, the model with M0 outperforms the random walk model for only brief periods of time (if at all). The monetary liquidity proxy cannot beat the random walk consistently in the sample, an instability that is also seen in figure 1e, depicting results of the Inoue and Rossi (2012) test. The results suggest that the predictive power of M0 depends heavily on the window size adopted in the exercise, implying a highly unstable relationship between monetary liquidity and the exchange rate. In addition, the above results are robust to the use of M1 or M2 as proxies. Indeed, the results are slightly worse when the latter two proxies for monetary liquidity are used.

Table 2e also shows the results of the tests for the long-term (10 years) treasury yield. The results in table 2e indicate a strong relationship between the long-term interest rate and the exchange rate. Based on the in-sample results, the long-term interest rate variable is statistically significant for 15 of the 27 countries in the sample. In addition, the Granger-causality test rejects the null hypothesis of non-causality for 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 1f shows that this relationship is robust for different periods of the sample but is more pronounced for the most recent years, notably after 2011. Figure 1g confirms that the relationship is robust to the window size chosen, based on the Inoue and Rossi (2012) test.

Tables 2f and 2g show the relationship between our proxies for risk taking and uncertainty and the exchange rate. Except for the TED spread, which exhibits a relatively weak relationship (although it is significant for some countries), these proxies show very strong and stable relationships with the exchange rate for almost all countries, with the R^2 and HR market timing test the highest among all indicators. In the HR test, the model consistently predicts exchange rate changes 56% of the time in the case of the VIX and 57% of the time in the case of the High Yield spread. The Granger-causality tests reject the null of non-causality for all countries for the VIX and the High Yield spread, confirming the predictive power of these variables. With respect to the TED spread, the Granger-causality test rejects the null for only four countries. Under the Granger-causality test that is robust to instabilities, this number rises to 20 countries, demonstrating the predictive power of the variable, although its relationship with the exchange rate is unstable.

Only a few remarks regarding the different proxies are necessary. The VIX has very high out-of-sample predictive power, especially for short periods, but the predictive power of the VIX falls when we consider longer forecasting horizons. The variable beats the random walk for nearly all countries in 1-week ahead forecasts. However, in 8-weeks ahead forecasting, the VIX outperforms the benchmark for only 14 countries. The HY indicator 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 1h and 1i confirm a more stable relationship between volatility and uncertainty and the exchange rate. Similar figures are obtained when we present the Inoue and Rossi (2012) tests.

Table 2h shows 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 almost all 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.

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 more closely examine effects on currencies, one important fact arises: the Japanese Yen and the Swiss Franc appear to behave differently than other currencies. Specifically, the results indicate that liquidity has a smaller impact on these currencies than on other currencies, with most proxies exhibiting non-significant relationships with these currencies. Even when the proxies show some predictive power with respect to these currencies, they tend to impact these currencies 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 do not suffer from liquidity issues and are viewed as safe-heavens, similarly to the U.S. dollar, in moments of turmoil.

6. CONCLUSIONS

This paper has examined the predictive power of several proxies for liquidity 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 some liquidity proxies exhibit both in-sample and out-of-sample predictability with respect to exchange rate dynamics.

Our results indicate that changes in funding liquidity of U.S. financial intermediaries impact exchange rates around the globe, yet its significance and the type of funding relevant to explaining exchange rate variations appears to vary over time. Overnight repurchase agreements (REPO) were significant predictors of exchange rate movements just after the financial crisis, while borrowings from other financial institutions were more important in the 2010-2012 period.

The paper also indicates that public (official) liquidity represented by U.S. monetary aggregates exert a minor and non-robust effect on exchange rates. By contrast, risk taking and long-term interest rate changes have strong and robust effects across time, proxies and exchange rates. Finally, the paper shows that common factors extracted from several liquidity indicators are useful in predicting exchange rate movements.

An important point has to be stressed with respect to the role of the recent U.S. monetary policy on the dynamics of the exchange rate around the globe. Although the paper indicates that changes in the monetary aggregates have a weak (direct) predictive power on movements of the exchange rate it might be the case that the large asset purchases implemented by the FED exert a significant indirect impact through changes in the long-term yields and investors' risk aversion. 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. Bekaert et. al. (2013) also show that the VIX is correlated with measures of monetary policy. Therefore, future research should analyze the role of the large asset purchases and non-traditional monetary policy in the dynamics of the exchange rate.

Yet, the results of the paper indicate that liquidity matters in forecasting exchange rates and that in some periods, liquidity is crucial to forecasting exchange rate movements.

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Table 1 – Correlation Among Liquidity Proxies

Table 1 shows the correlation among the different liquidity measures adopted throughout the paper. COMMERCIAL is the total outstanding stock of commercial papers. REPO is total outstanding overnight repurchase agreements of US financial intermediaries. DEPOSITS is the total resident deposits in the banking sector. SPREAD is the spread between the domestic deposit rate for deposits with a maturity of up to one year and the 6-month interbank interest rate. BORROWINGS is the total loans and securities of financial institutions from other financial intermediaries. CREDIT is total bank credit to the non-financial private sector. M0, M1, and M2 represent monetary aggregates. T10Y is the 10 years 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.

Variable	COMMERCIAL	REPO	DEPOSITS	SPREAD	BORROWINGS	CREDIT	M0	M1	M2	T10Y	VIX	TED	HY	ML	MLE
COMMERCIAL	1.00														
REPO	0.18	1.00													
DEPOSITS	-0.28	-0.29	1.00												
SPREAD	-0.10	-0.27	0.04	1.00											
BORROWINGS	0.03	0.04	0.05	0.16	1.00										
CREDIT	-0.27	0.08	0.50	-0.18	0.01	1.00									
M0	-0.24	-0.39	0.45	0.33	0.22	0.03	1.00								
M1	-0.16	-0.31	0.58	0.18	0.04	0.09	0.50	1.00							
M2	-0.23	-0.28	0.72	0.16	0.11	0.26	0.50	0.73	1.00						
T10Y	0.01	-0.05	-0.13	-0.34	-0.01	-0.16	-0.05	-0.08	-0.14	1.00					
VIX	-0.17	0.05	0.33	-0.24	-0.04	0.36	0.16	0.17	0.24	-0.20	1.00				
TED	-0.06	0.18	0.13	-0.55	-0.04	0.35	-0.14	-0.03	0.00	-0.04	0.52	1.00			
HY	-0.11	-0.01	0.31	-0.05	0.06	0.34	0.22	0.19	0.28	-0.29	0.88	0.43	1.00		
ML	0.12	-0.02	-0.25	0.06	-0.09	-0.36	-0.18	-0.16	-0.25	0.33	-0.80	-0.60	-0.93	1.00	
MLE	0.17	0.00	-0.31	-0.13	-0.16	-0.37	-0.32	-0.22	-0.33	0.44	-0.69	-0.36	-0.85	0.90	1.00

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

Table 2a shows the results from the in-sample and out-of-sample exercises. OLS and R^2 stand for the coefficient and the R^2 of the estimation of (1). HR represents 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 is the p-value of the Rossi (2005) Granger-Causality test that is robust to instabilities. Table 2a 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.

	REPO										COMMERCIAL									
	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
Countries	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**0.044***	0.012	58.1%	0.010	0.020	**0.993**	0.010	**0.989**	**0.982**	**0.991**	0.006	0.000	57.5%	0.720	0.320	1.013	0.720	1.011	1.015	1.013
Canada	**0.044***	0.024	55.5%	0.000	0.060	**0.991**	0.000	**0.986**	**0.976**	**0.982**	-0.001	0.000	54.7%	0.930	0.670	1.014	0.850	1.013	1.014	1.011
Japan	0.009	0.001	49.5%	0.470	0.590	1.012	0.960	1.010	1.009	1.005	0.003	0.000	56.9%	0.770	1.000	1.013	0.930	1.012	1.013	1.013
New Zealand	**0.043***	0.010	54.4%	0.020	0.030	**0.995**	0.020	**0.989**	**0.983**	**0.992**	-0.002	0.000	53.8%	0.910	0.620	1.020	0.880	1.013	1.013	1.009
Sweden	**0.029****	0.006	53.9%	0.050	0.310	1.000	0.110	**0.996**	**0.992**	**1.000**	0.012	0.002	55.2%	0.380	0.450	1.008	0.720	1.007	1.005	1.004
UK	**0.037***	0.016	53.6%	0.000	0.150	**0.994**	0.010	**0.996**	**0.992**	1.002	0.012	0.003	51.6%	0.340	0.080	1.011	0.730	1.014	1.016	1.014
Switzerland	0.033	0.010	52.7%	0.030	0.280	1.001	0.110	**0.996**	**0.996**	1.002	-0.003	0.000	55.9%	0.780	0.720	1.014	0.780	1.012	1.011	1.010
Norway	**0.049***	0.018	57.2%	0.000	0.030	**0.994**	0.010	**0.990**	**0.988**	**0.999**	0.008	0.001	52.5%	0.520	0.250	1.010	0.670	1.008	1.008	1.008
Denmark	**0.028****	0.008	54.8%	0.030	0.130	1.004	0.130	**0.994**	**0.991**	**0.997**	0.004	0.000	51.1%	0.740	0.630	1.013	0.800	1.012	1.016	1.012
Israel	0.002	0.000	52.5%	0.860	1.000	1.005	0.850	1.004	1.002	1.004	-0.007	0.001	50.2%	0.490	0.840	1.010	0.940	1.008	1.006	1.006
Brazil	**0.047****	0.009	48.8%	0.020	0.110	**0.992**	0.010	**0.990**	**0.988**	**0.997**	0.002	0.000	57.5%	0.920	1.000	1.013	0.900	1.012	1.016	1.016
South Africa	**0.077***	0.022	54.4%	0.000	0.000	**0.993**	0.010	**0.982**	**0.972**	**0.978**	-0.003	0.000	46.7%	0.870	0.420	1.016	0.970	1.016	1.016	1.012
Turkey	0.009	0.000	46.1%	0.770	0.530	**0.978**	0.070	**0.995**	**0.991**	**0.999**	0.004	0.000	46.1%	0.810	0.740	1.017	0.930	1.016	1.018	1.012
Russia	0.006	0.001	52.7%	0.580	0.720	1.004	0.890	1.004	1.003	1.003	0.013	0.005	51.4%	0.180	0.340	1.006	0.640	1.005	1.006	1.006
South Korea	**0.047***	0.024	55.0%	0.000	0.070	**0.991**	0.010	**0.986**	**0.981**	**0.993**	-0.002	0.000	52.2%	0.890	0.670	1.013	0.860	1.012	1.013	1.009
Mexico	0.007	0.000	46.6%	0.670	0.620	1.004	0.840	1.003	1.001	1.002	-0.005	0.000	46.7%	0.690	1.000	1.010	0.870	1.007	1.006	1.003
Singapore	0.016	0.011	54.7%	0.000	0.170	**0.997**	0.040	**0.992**	**0.989**	**0.996**	0.003	0.000	54.8%	0.610	0.810	1.007	0.520	1.005	1.005	1.005
Phillipines	**0.023***	0.017	56.3%	0.000	0.000	**0.991**	0.000	**0.984**	**0.977**	**0.987**	0.000	0.000	50.2%	0.950	0.230	1.008	0.600	1.007	1.006	1.006
Poland	**0.036****	0.007	54.1%	0.060	0.390	1.000	0.120	**1.001**	**0.998**	1.003	0.009	0.001	53.1%	0.630	0.500	1.014	0.950	1.011	1.011	1.008
Taiwan	0.008	0.004	49.5%	0.150	0.640	1.000	0.230	**0.999**	**0.999**	1.004	0.005	0.003	51.1%	0.260	0.210	1.011	0.750	1.008	1.007	1.008
Chile	**0.028***	0.006	51.3%	0.070	0.380	**0.997**	0.060	**0.996**	**0.991**	**0.996**	-0.006	0.000	52.5%	0.710	0.550	1.014	0.830	1.012	1.015	1.012
Hungary	0.031	0.005	53.6%	0.120	0.440	1.004	0.260	**0.997**	**0.994**	**0.999**	0.006	0.000	54.2%	0.740	0.730	1.013	0.940	1.012	1.012	1.009
Czech	0.024	0.004	56.6%	0.150	0.410	1.005	0.330	**1.001**	**0.998**	1.002	0.012	0.002	55.2%	0.410	0.630	1.009	0.670	1.008	1.008	1.008
Colombia	0.015	0.002	49.8%	0.330	0.270	1.001	0.330	**1.000**	**0.999**	**1.001**	0.018	0.005	52.7%	0.210	0.630	1.009	0.740	1.006	1.008	1.007
Peru	0.006	0.002	55.5%	0.380	0.390	1.000	0.210	**1.000**	**0.996**	**0.997**	0.007	0.004	56.1%	0.180	0.700	1.008	0.480	1.005	1.007	1.006
Indonesia	**0.033***	0.012	52.2%	0.000	0.040	**0.990**	0.000	**0.989**	**0.989**	**0.996**	-0.015	0.004	50.5%	0.110	0.790	1.010	0.460	1.005	1.001	1.004
Thailand	0.006	0.001	54.1%	0.370	0.510	1.003	0.130	**0.998**	**0.995**	**0.998**	-0.001	0.000	54.2%	0.810	0.230	1.005	0.300	1.002	1.001	1.002

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

Table 2b shows the results from the in-sample and out-of-sample exercises. OLS 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 2b 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.

	DEPOSITS										SPREAD									
	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
Countries	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	-0.022	0.000	57.0%	0.820	1.000	1.005	0.630	1.004	1.005	1.005	3.308	0.011	55.8%	0.430	0.820	1.029	0.860	1.008	1.003	1.003
Canada	0.018	0.000	54.5%	0.780	1.000	1.007	0.810	1.005	1.004	1.003	1.683	0.006	54.4%	0.510	0.460	1.022	0.840	1.003	1.002	1.004
Japan	-0.036	0.001	48.3%	0.560	0.830	1.006	0.480	1.001	**0.998**	**0.992**	-1.359	0.004	49.1%	0.440	1.000	1.013	0.800	1.004	1.006	1.002
New Zealand	0.021	0.000	57.0%	0.850	0.760	1.006	0.760	1.005	1.005	1.006	3.768	0.013	55.8%	0.250	0.460	1.013	0.590	1.016	1.009	1.007
Sweden	-0.005	0.000	54.2%	0.940	0.690	1.006	0.780	1.006	1.006	1.007	1.650	0.003	53.4%	0.410	1.000	1.010	0.860	1.005	1.001	1.002
UK	0.010	0.000	48.3%	0.910	1.000	1.009	0.900	1.007	1.007	1.009	0.642	0.001	50.2%	0.770	0.570	1.023	0.970	1.013	1.007	1.005
Switzerland	-0.028	0.000	52.3%	0.720	0.630	1.005	0.570	1.003	1.003	1.002	-1.115	0.002	50.6%	0.410	1.000	1.011	0.700	1.010	1.003	1.001
Norway	0.009	0.000	55.8%	0.920	1.000	1.006	0.740	1.005	1.005	1.004	0.425	0.000	56.1%	0.810	0.540	1.013	0.790	1.008	1.004	1.005
Denmark	-0.020	0.000	53.1%	0.780	1.000	1.007	0.650	1.005	1.005	1.004	0.534	0.000	51.9%	0.760	0.740	1.022	0.880	1.014	1.007	1.005
Israel	0.061	0.002	51.6%	0.370	0.600	1.006	0.870	1.005	1.005	1.004	**2.97***	0.020	53.9%	0.010	0.190	**0.994**	0.090	**0.993**	**0.992**	**0.998**
Brazil	-0.025	0.000	49.1%	0.820	1.000	1.009	0.910	1.009	1.009	1.006	0.760	0.000	47.8%	0.860	0.630	1.030	0.820	1.011	1.007	1.005
South Africa	0.002	0.000	47.3%	0.950	1.000	1.010	0.930	1.010	1.010	1.009	1.626	0.002	46.3%	0.610	0.810	1.025	0.930	1.014	1.016	1.014
Turkey	0.058	0.000	46.1%	0.620	1.000	1.010	0.900	1.008	1.008	1.005	2.453	0.002	45.9%	0.460	0.710	1.024	0.810	1.015	1.016	1.013
Russia	0.056	0.002	47.8%	0.410	0.730	1.005	0.830	1.003	1.004	1.005	-0.197	0.000	51.1%	0.880	0.750	1.007	0.970	1.004	1.003	1.002
South Korea	0.012	0.000	55.0%	0.900	0.680	1.008	0.920	1.007	1.008	1.007	-0.019	0.000	53.4%	0.950	0.300	1.020	0.850	1.012	1.010	1.005
Mexico	0.096	0.004	49.5%	0.220	0.680	1.002	0.440	**0.999**	**0.998**	**0.996**	3.689	0.021	44.2%	0.290	0.700	1.019	0.680	1.011	1.005	1.002
Singapore	0.010	0.000	54.8%	0.780	0.780	1.003	0.350	**1.000**	**0.997**	**0.998**	0.524	0.002	52.3%	0.500	0.260	1.007	0.540	**0.999**	**0.997**	**0.995**
Phillipines	-0.029	0.001	52.7%	0.420	1.000	1.001	0.260	**0.999**	**1.000**	1.000	0.471	0.001	50.0%	0.470	1.000	1.002	0.380	**1.000**	**0.999**	**0.998**
Poland	0.059	0.001	55.2%	0.590	0.680	1.006	0.860	1.005	1.006	1.005	1.311	0.001	51.7%	0.700	0.870	1.021	0.950	1.012	1.009	1.005
Taiwan	0.004	0.000	49.8%	0.890	0.820	1.002	0.430	1.001	1.002	1.003	0.713	0.005	50.8%	0.210	0.290	1.003	0.320	**0.999**	1.002	**1.000**
Chile	-0.045	0.001	53.0%	0.620	1.000	1.004	0.760	1.003	1.004	1.003	0.882	0.001	52.5%	0.780	0.400	1.031	0.780	1.014	1.020	1.011
Hungary	0.097	0.002	50.9%	0.410	1.000	1.005	0.800	1.004	1.005	1.004	**3.38****	0.008	51.7%	0.270	0.350	1.010	0.700	1.001	1.006	1.004
Czech	0.002	0.000	55.5%	0.950	0.880	1.007	0.660	1.004	1.004	1.004	0.085	0.000	55.5%	0.950	0.850	1.018	0.840	1.012	1.007	1.002
Colombia	-0.055	0.001	53.9%	0.600	1.000	1.007	0.880	1.005	1.006	1.005	1.210	0.002	53.6%	0.580	0.600	1.012	0.820	1.008	1.005	1.001
Peru	-0.027	0.002	56.6%	0.530	1.000	1.006	0.590	1.002	1.001	**0.999**	0.147	0.000	56.7%	0.860	0.490	1.011	0.750	**1.000**	**0.998**	**0.995**
Indonesia	0.074	0.003	51.6%	0.220	0.110	1.006	0.740	1.005	1.005	1.005	0.843	0.001	51.4%	0.580	0.500	1.006	0.480	1.002	1.002	1.002
Thailand	-0.047	0.004	56.3%	0.060	0.070	**1.001**	0.060	**0.991**	**0.987**	**0.990**	**1.07***	0.008	53.9%	0.020	0.130	**0.997**	0.050	**0.995**	**0.994**	**0.995**

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

Table 2c shows the results of the in-sample and out-of-sample exercises. OLS 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 2c 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.

	BORROWINGS										CREDIT									
	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
Countries	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**-0.018***	0.005	55.9%	0.060	0.170	1.001	0.110	**0.999**	**0.999**	**0.997**	0.055	0.001	55.5%	0.600	1.000	1.009	0.800	1.006	1.007	1.006
Canada	**-0.011****	0.003	54.7%	0.170	0.610	1.003	0.370	1.001	1.001	**0.999**	0.067	0.003	53.1%	0.380	0.840	1.010	0.600	1.004	1.003	1.004
Japan	0.007	0.001	49.2%	0.350	0.890	1.006	0.920	1.006	1.004	1.001	-0.080	0.004	49.4%	0.210	0.830	1.005	0.310	**0.998**	**0.996**	**0.992**
New Zealand	-0.008	0.001	56.3%	0.490	0.590	1.006	0.730	1.004	1.004	1.003	0.067	0.001	55.8%	0.530	1.000	1.010	0.870	1.006	1.005	1.005
Sweden	**-0.019***	0.007	53.1%	0.070	0.570	1.003	0.220	**0.999**	**0.998**	**0.995**	0.049	0.001	54.2%	0.560	1.000	1.009	0.830	1.006	1.006	1.007
UK	-0.002	0.000	46.6%	0.770	0.540	1.009	0.780	1.007	1.006	1.004	0.026	0.000	50.0%	0.730	0.310	1.011	0.710	1.008	1.009	1.008
Switzerland	-0.005	0.001	51.7%	0.600	1.000	1.004	0.590	1.003	1.001	**0.998**	-0.023	0.000	52.2%	0.700	0.830	1.005	0.710	1.004	1.004	1.003
Norway	**-0.021***	0.008	54.7%	0.030	0.500	**1.001**	0.090	**0.995**	**0.994**	**0.990**	0.069	0.002	53.9%	0.370	0.850	1.006	0.550	1.002	1.003	1.003
Denmark	-0.011	0.003	52.3%	0.230	0.630	1.003	0.370	1.002	**1.000**	**0.998**	-0.008	0.000	52.2%	0.910	1.000	1.009	0.860	1.008	1.009	1.008
Israel	**-0.010****	0.003	53.4%	0.170	0.700	1.003	0.650	1.001	1.001	**1.000**	0.032	0.001	49.8%	0.570	1.000	1.007	0.830	1.006	1.005	1.006
Brazil	**-0.021***	0.004	54.7%	0.070	0.600	1.003	0.350	**0.999**	**0.998**	**0.999**	-0.005	0.000	47.8%	0.950	1.000	1.016	0.930	1.012	1.011	1.009
South Africa	-0.013	0.002	49.1%	0.280	1.000	1.006	0.760	1.004	1.003	1.002	0.046	0.000	50.0%	0.700	1.000	1.013	0.970	1.013	1.013	1.012
Turkey	-0.001	0.000	46.1%	0.900	1.000	1.006	0.980	1.004	1.004	1.004	0.086	0.001	45.9%	0.470	1.000	1.016	0.570	1.008	1.006	1.004
Russia	**-0.016***	0.009	50.9%	0.030	0.000	1.001	0.160	**0.999**	**0.999**	**1.000**	0.087	0.006	48.8%	0.110	0.020	1.002	0.300	**0.998**	**0.998**	**1.000**
South Korea	-0.008	0.001	49.7%	0.430	0.620	1.006	0.840	1.006	1.005	1.004	0.088	0.004	53.3%	0.330	0.840	1.011	0.680	1.007	1.004	1.003
Mexico	-0.009	0.002	49.4%	0.330	1.000	1.003	0.770	1.002	1.001	1.001	0.104	0.006	48.1%	0.250	0.850	1.007	0.340	**0.997**	**0.994**	**0.994**
Singapore	-0.002	0.001	54.8%	0.580	1.000	1.002	0.270	**1.000**	**0.999**	**0.999**	-0.006	0.000	55.0%	0.860	1.000	1.004	0.460	1.002	1.002	1.001
Phillipines	0.004	0.001	48.1%	0.430	0.560	1.004	0.360	**0.999**	**0.998**	**0.998**	0.025	0.001	50.3%	0.470	0.800	1.002	0.450	1.001	1.001	**1.000**
Poland	**-0.025***	0.008	51.9%	0.060	0.610	1.002	0.210	**0.998**	**0.998**	**0.997**	0.094	0.002	52.5%	0.410	1.000	1.008	0.610	1.002	1.001	1.001
Taiwan	-0.005	0.003	49.2%	0.200	0.310	1.001	0.220	**1.000**	**0.998**	**0.995**	0.005	0.000	50.0%	0.860	0.830	1.006	0.720	1.004	1.003	1.004
Chile	-0.004	0.000	53.6%	0.680	0.810	1.004	0.820	1.003	1.001	1.001	-0.013	0.000	53.8%	0.900	0.710	1.009	0.900	1.007	1.008	1.007
Hungary	**-0.028**	0.009	50.6%	0.040	0.700	1.000	0.150	**0.998**	**0.998**	**0.996**	0.061	0.001	49.8%	0.580	1.000	1.008	0.840	1.006	1.006	1.006
Czech	**-0.020****	0.006	54.2%	0.060	0.470	1.001	0.130	**0.997**	**0.995**	**0.994**	0.023	0.000	55.5%	0.770	1.000	1.007	0.720	1.004	1.004	1.003
Colombia	0.003	0.000	55.0%	0.740	0.770	1.004	0.870	1.003	1.004	1.005	-0.029	0.000	57.7%	0.720	1.000	1.005	0.900	1.005	1.006	1.005
Peru	**-0.005****	0.004	54.8%	0.060	0.030	1.002	0.130	**0.998**	**0.993**	**0.990**	0.000	0.000	56.4%	0.950	0.720	1.001	0.310	**0.999**	**0.998**	**0.999**
Indonesia	-0.003	0.000	51.1%	0.680	0.200	1.007	0.570	1.005	1.003	1.001	0.114	0.007	54.4%	0.110	0.070	1.009	0.470	1.006	1.006	1.006
Thailand	0.001	0.000	54.2%	0.770	0.380	1.001	0.220	**0.999**	**0.998**	**0.999**	-0.005	0.000	54.2%	0.820	0.780	1.004	0.270	**0.999**	**0.997**	**0.999**

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

Table 2d shows the results from the in-sample and out-of-sample exercises. OLS 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 2d 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% level of significance. Bold values in the out-of-sample exercise mean that the model beats the benchmark at 10% level of significance.

	M0										M1									
Countries	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	**-0.283****	0.009	53.4%	0.050	0.060	**0.998**	0.100	**0.995**	**0.994**	**0.995**	-0.026	0.000	57.0%	0.730	0.650	1.005	0.290	**0.993**	**0.991**	**0.996**
Canada	**-0.163****	0.006	53.0%	0.110	0.420	1.001	0.250	**0.999**	**0.997**	**0.995**	-0.044	0.002	53.3%	0.320	0.560	1.006	0.300	**0.998**	**0.994**	**0.996**
Japan	0.061	0.001	49.7%	0.540	0.880	1.004	0.780	1.004	1.004	1.003	0.044	0.002	53.1%	0.280	0.670	1.002	0.410	1.002	1.002	1.001
New Zealand	**-0.268****	0.007	57.0%	0.070	0.630	1.001	0.280	**0.999**	**0.998**	**0.997**	-0.008	0.000	56.9%	0.920	0.620	1.008	0.530	1.001	1.000	1.001
Sweden	-0.190	0.005	52.3%	0.160	0.270	1.006	0.550	1.005	1.005	1.004	-0.003	0.000	54.2%	0.940	0.770	1.008	0.610	1.002	1.002	1.003
UK	**-0.191***	0.008	53.3%	0.070	0.290	1.004	0.360	**1.000**	**0.998**	**0.998**	-0.030	0.001	51.1%	0.520	0.730	1.008	0.510	**0.998**	**0.998**	1.005
Switzerland	-0.101	0.002	51.9%	0.360	0.820	1.004	0.600	1.002	1.002	1.002	-0.014	0.000	51.6%	0.820	0.130	1.008	0.570	1.004	1.002	1.002
Norway	**-0.264***	0.009	52.3%	0.030	0.460	1.000	0.140	**0.996**	**0.995**	**0.995**	-0.060	0.003	55.5%	0.250	0.800	1.007	0.380	**0.998**	**0.998**	1.001
Denmark	**-0.190****	0.007	52.0%	0.060	0.450	1.004	0.350	1.001	**1.000**	**0.999**	-0.023	0.001	51.9%	0.630	0.680	1.009	0.490	1.002	**0.998**	**0.998**
Israel	0.005	0.000	53.0%	0.950	0.460	1.012	1.000	1.012	1.011	1.013	0.052	0.003	53.3%	0.280	0.140	1.007	0.740	1.006	1.006	1.004
Brazil	-0.287	0.006	51.4%	0.050	0.100	**0.999**	0.090	**0.999**	**0.995**	**0.996**	-0.114	0.005	51.7%	0.160	0.890	1.004	0.280	**0.998**	**1.000**	1.004
South Africa	**-0.292****	0.006	50.5%	0.070	0.290	1.002	0.400	1.001	1.002	1.002	0.014	0.000	47.8%	0.860	0.600	1.008	0.910	1.005	1.004	1.004
Turkey	-0.203	0.001	46.9%	0.160	0.240	1.003	0.560	1.003	1.004	1.004	-0.072	0.001	46.9%	0.360	1.000	1.007	0.610	1.002	1.002	1.003
Russia	-0.039	0.000	53.1%	0.740	0.120	1.008	0.960	1.008	1.009	1.010	0.033	0.002	47.7%	0.560	0.730	1.008	0.890	1.005	1.006	1.007
South Korea	**-0.307****	0.017	51.9%	0.010	0.120	1.000	0.150	**0.995**	**0.996**	**0.996**	-0.072	0.005	51.7%	0.210	0.390	1.005	0.300	**0.997**	**0.995**	**0.998**
Mexico	-0.057	0.001	46.7%	0.660	0.060	1.003	0.860	1.003	1.004	1.004	-0.001	0.000	46.3%	0.950	0.660	1.005	0.970	1.005	1.004	1.003
Singapore	-0.041	0.001	54.7%	0.410	0.310	1.002	0.300	**0.996**	**0.999**	**0.999**	0.011	0.000	55.2%	0.690	0.500	1.003	0.330	**0.998**	**0.995**	**0.995**
Phillipines	**-0.135***	0.010	53.9%	0.010	0.010	**1.000**	0.080	**0.994**	**0.991**	**0.991**	-0.031	0.003	52.7%	0.220	0.180	1.003	0.170	**0.993**	**0.992**	**0.995**
Poland	-0.115	0.001	52.7%	0.490	0.700	1.006	0.890	1.006	1.007	1.007	-0.008	0.000	54.5%	0.920	1.000	1.007	0.870	1.005	1.004	1.005
Taiwan	-0.044	0.002	49.8%	0.330	0.650	1.005	0.660	1.005	1.005	1.006	-0.006	0.000	50.2%	0.760	0.050	1.005	0.450	**0.998**	**0.999**	1.002
Chile	**-0.297***	0.012	52.5%	0.030	0.170	**0.999**	0.090	**0.993**	**0.992**	**0.992**	**-0.104****	0.008	52.7%	0.060	0.150	**0.999**	0.080	**0.993**	**0.995**	**0.997**
Hungary	-0.108	0.001	51.3%	0.560	1.000	1.005	0.900	1.005	1.005	1.005	0.008	0.000	53.6%	0.930	1.000	1.007	0.770	1.005	1.003	1.003
Czech	-0.151	0.003	54.8%	0.300	0.570	1.006	0.640	1.005	1.005	1.005	0.003	0.000	55.5%	0.940	1.000	1.006	0.660	1.004	1.002	1.002
Colombia	-0.104	0.002	53.1%	0.550	0.490	1.007	0.540	1.003	1.002	1.002	-0.075	0.004	53.3%	0.250	0.680	1.005	0.390	1.001	1.000	1.000
Peru	-0.091	0.008	53.6%	0.210	0.110	1.002	0.230	**0.998**	**0.997**	**1.000**	-0.011	0.001	56.6%	0.620	1.000	1.005	0.520	1.002	**1.000**	**0.999**
Indonesia	-0.100	0.002	52.7%	0.280	0.360	1.003	0.620	1.003	1.003	1.003	0.011	0.000	47.5%	0.820	0.170	1.009	0.800	1.005	1.003	1.003
Thailand	-0.061	0.003	55.6%	0.180	0.120	1.005	0.230	1.001	**0.999**	**1.000**	-0.025	0.002	54.1%	0.210	0.070	1.005	0.100	**0.993**	**0.991**	**0.995**

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

Table 2e shows the results from the in-sample and out-of-sample exercises. OLS 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 2e 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.

	M2										T10Y									
Countries	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks
Australia	-0.207	0.005	55.9%	0.160	0.520	1.004	0.160	**0.994**	**0.995**	**0.994**	-2.76*	0.025	51.9%	0.000	0.000	**0.990**	0.000	**0.976**	**0.999**	**0.997**
Canada	-0.108	0.003	54.7%	0.230	0.640	1.005	0.330	**0.999**	**0.997**	**0.996**	-2.67*	0.048	54.5%	0.000	0.000	**0.997**	0.000	**0.978**	**0.988**	**0.992**
Japan	0.107	0.003	49.4%	0.220	1.000	1.004	0.520	1.002	1.001	**1.000**	4.09*	0.109	60.6%	0.000	0.000	**0.916**	0.000	**0.944**	**0.965**	**0.980**
New Zealand	-0.102	0.001	56.7%	0.520	0.680	1.007	0.470	1.002	1.002	1.001	-2.78*	0.023	53.3%	0.000	0.000	**0.982**	0.000	**0.997**	**1.000**	**1.000**
Sweden	-0.104	0.002	53.4%	0.430	1.000	1.007	0.480	1.003	1.003	1.003	-0.987	0.003	52.3%	0.220	0.000	**0.996**	0.070	**0.998**	**1.001**	1.005
UK	-0.076	0.001	51.6%	0.480	0.530	1.010	0.620	1.004	1.001	1.002	-1.031	0.007	54.1%	0.160	0.000	**0.999**	0.040	1.002	1.006	1.007
Switzerland	0.047	0.000	51.7%	0.740	0.660	1.006	0.570	1.003	1.003	1.002	1.45**	0.010	53.1%	0.040	0.000	1.004	0.300	**0.996**	**0.997**	**1.000**
Norway	-0.141	0.003	55.0%	0.250	0.600	1.005	0.200	**0.997**	**0.997**	**0.997**	-0.984	0.004	52.0%	0.220	0.000	**0.992**	0.010	**0.993**	**0.999**	1.002
Denmark	-0.053	0.001	52.3%	0.610	0.660	1.007	0.420	1.001	**0.999**	**0.998**	0.288	0.000	52.7%	0.650	0.000	1.004	0.510	**0.999**	**1.000**	1.004
Israel	0.091	0.002	50.3%	0.370	0.860	1.006	0.920	1.005	1.006	1.007	-0.900	0.006	54.1%	0.120	0.000	1.002	0.630	1.001	1.003	1.003
Brazil	-0.347*	0.010	52.7%	0.010	0.060	1.003	0.130	**0.997**	1.001	1.002	-5.67*	0.071	57.8%	0.000	0.000	**0.942**	0.000	**0.979**	**0.988**	**0.996**
South Africa	-0.133	0.001	49.4%	0.430	0.590	1.008	0.310	1.002	1.001	1.002	-2.42*	0.012	53.4%	0.030	0.000	**0.990**	0.020	**0.997**	**1.001**	**0.997**
Turkey	-0.286**	0.003	50.8%	0.110	0.900	1.009	0.560	1.006	1.008	1.012	-1.072	0.001	47.2%	0.370	0.000	1.003	0.270	1.001	1.002	1.003
Russia	0.086	0.002	46.4%	0.470	0.750	1.007	0.830	1.006	1.007	1.008	-2.16*	0.039	52.3%	0.000	0.000	**0.973**	0.000	**0.989**	**0.997**	**1.000**
South Korea	-0.169	0.006	51.3%	0.130	0.260	1.005	0.230	**0.992**	**0.999**	1.001	-2.03*	0.023	53.3%	0.000	0.020	**0.991**	0.040	1.002	1.002	**0.999**
Mexico	0.000	0.000	46.3%	0.950	0.590	1.006	0.960	1.006	1.006	1.006	-3.11*	0.050	54.5%	0.000	0.000	**0.973**	0.000	**0.990**	**0.992**	**0.994**
Singapore	0.027	0.001	54.7%	0.620	0.260	1.003	0.300	**0.999**	**0.997**	**0.996**	-0.188	0.001	55.2%	0.570	0.190	**0.995**	0.050	**0.997**	**0.996**	**0.996**
Phillipines	-0.019	0.000	50.3%	0.720	0.820	1.003	0.320	**0.999**	**0.998**	**0.998**	-0.778*	0.011	54.4%	0.020	0.230	**0.992**	0.010	**1.000**	**0.997**	**0.996**
Poland	-0.021	0.000	54.5%	0.910	0.790	1.007	0.820	1.005	1.005	1.006	-2.43*	0.016	50.2%	0.010	0.000	**0.988**	0.010	**0.994**	**1.000**	1.002
Taiwan	-0.022	0.001	50.0%	0.600	0.270	1.006	0.350	1.001	1.002	1.003	-0.679*	0.016	52.7%	0.010	0.040	**0.989**	0.020	**0.995**	**0.998**	**0.996**
Chile	-0.230**	0.008	53.9%	0.060	0.280	1.002	0.130	**0.994**	**0.993**	**0.991**	-2.86*	0.035	50.8%	0.000	0.000	**0.986**	0.000	1.006	1.003	**0.998**
Hungary	0.027	0.000	54.5%	0.890	0.860	1.006	0.760	1.004	1.004	1.004	-0.798	0.002	48.9%	0.420	0.000	**0.998**	0.013	**0.996**	**0.999**	1.003
Czech	0.013	0.000	55.5%	0.930	1.000	1.006	0.620	1.004	1.003	1.002	-0.226	0.000	55.6%	0.760	0.000	1.002	0.290	**0.998**	**0.999**	1.002
Colombia	-0.149	0.004	52.0%	0.280	0.560	1.006	0.500	1.001	1.001	1.003	-1.72*	0.014	54.5%	0.010	0.130	**0.994**	0.020	1.003	**1.000**	**1.000**
Peru	-0.058	0.004	55.6%	0.230	1.000	1.002	0.250	**0.998**	**0.997**	**0.997**	-0.271	0.002	57.7%	0.230	0.180	1.001	0.350	**0.999**	**0.998**	**0.999**
Indonesia	-0.020	0.000	50.9%	0.820	0.460	1.008	0.390	1.002	1.002	1.005	0.039	0.000	46.4%	0.940	0.340	1.005	0.830	1.007	1.008	1.006
Thailand	-0.051	0.002	55.5%	0.220	0.290	1.007	0.150	**0.994**	**0.991**	**0.992**	0.089	0.000	54.2%	0.720	0.580	1.001	0.220	**0.998**	**0.996**	**0.998**

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

Table 2f shows the results from the in-sample and out-of-sample exercises. OLS 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 2f 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.

	VIX										TED									
Countries	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	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**	**3.37***	0.052	55.8%	0.030	0.020	**0.982**	0.050	1.004	**0.995**	1.002
Canada	**0.041***	0.144	60.3%	0.000	0.000	**0.897**	0.000	**0.967**	**0.996**	**1.000**	0.797	0.006	54.2%	0.470	0.660	1.010	0.630	1.013	**1.000**	1.003
Japan	**-0.023***	0.045	53.4%	0.000	0.000	**0.966**	0.000	**0.997**	**0.994**	**1.000**	-0.787	0.005	49.4%	0.350	0.030	1.009	0.220	1.012	1.006	1.007
New Zealand	**0.056***	0.121	58.3%	0.000	0.000	**0.910**	0.000	**0.986**	**1.000**	1.004	**2.55***	0.026	57.2%	0.120	0.000	**1.002**	0.080	1.017	1.003	1.011
Sweden	**0.034***	0.060	53.0%	0.000	0.000	**0.953**	0.000	**0.991**	**0.998**	1.001	0.637	0.002	53.6%	0.540	0.080	1.012	0.510	1.013	1.005	1.004
UK	**0.013***	0.013	49.7%	0.000	0.030	**0.990**	0.010	**1.000**	1.008	1.005	-0.106	0.000	51.7%	0.920	0.000	1.016	0.970	1.014	1.002	1.005
Switzerland	-0.003	0.001	52.2%	0.560	0.020	1.002	0.310	1.003	1.001	1.001	-0.141	0.000	51.7%	0.810	0.010	1.010	0.760	1.006	1.001	**1.000**
Norway	**0.027***	0.038	51.9%	0.000	0.000	**0.960**	0.000	**0.993**	**1.000**	1.001	0.569	0.002	54.5%	0.560	0.260	1.010	0.650	1.014	1.006	1.002
Denmark	**0.014***	0.014	50.9%	0.000	0.000	**0.983**	0.000	**0.999**	**1.000**	1.002	-0.014	0.001	51.4%	0.760	0.090	1.016	0.930	1.013	1.003	1.001
Israel	**0.028***	0.074	58.4%	0.000	0.000	**0.962**	0.000	1.001	1.008	1.005	-0.355	0.001	50.9%	0.620	0.000	1.009	0.780	1.004	**0.999**	1.003
Brazil	**0.073***	0.151	62.0%	0.000	0.000	**0.892**	0.000	**0.966**	**0.989**	**0.999**	**3.37***	0.034	55.3%	0.030	0.000	**0.982**	0.070	**0.982**	**0.991**	1.002
South Africa	**0.058***	0.088	56.1%	0.000	0.000	**0.917**	0.000	**0.983**	**0.998**	**0.998**	1.073	0.003	49.8%	0.490	0.020	1.013	0.460	1.023	1.011	1.009
Turkey	**0.074***	0.075	59.4%	0.000	0.000	**0.888**	0.000	**0.983**	**0.999**	1.002	1.541	0.003	47.2%	0.390	0.120	1.020	0.400	1.029	1.007	1.010
Russia	**0.024***	0.061	54.7%	0.000	0.000	**0.965**	0.000	**0.995**	**1.000**	1.003	-0.055	0.000	51.9%	0.920	0.100	1.006	0.990	1.006	1.003	1.002
South Korea	**0.036***	0.092	57.7%	0.000	0.000	**0.943**	0.000	**0.986**	**0.999**	1.003	**1.60****	0.020	58.3%	0.130	0.000	1.001	0.250	1.005	1.005	1.002
Mexico	**0.052***	0.176	60.3%	0.000	0.000	**0.879**	0.000	**0.964**	**0.987**	**0.999**	**1.91***	0.025	49.8%	0.120	0.400	**0.996**	0.095	1.001	**0.998**	1.006
Singapore	**0.016***	0.077	55.9%	0.000	0.000	**0.939**	0.000	**0.981**	**0.996**	**0.997**	0.491	0.008	54.8%	0.120	0.000	**0.998**	0.090	**0.990**	**0.996**	**0.995**
Phillipines	**0.018***	0.070	54.5%	0.000	0.000	**0.946**	0.000	**0.989**	**0.999**	1.002	0.355	0.003	51.3%	0.340	0.000	1.006	0.300	1.005	**0.998**	**0.997**
Poland	**0.053***	0.100	55.8%	0.000	0.000	**0.929**	0.000	**0.987**	**0.995**	**0.999**	0.193	0.000	54.1%	0.910	0.040	1.014	0.840	1.014	1.002	1.003
Taiwan	**0.010***	0.045	55.8%	0.000	0.000	**0.961**	0.000	**0.992**	**0.998**	**1.000**	0.237	0.003	50.9%	0.460	0.000	1.010	0.360	1.008	1.003	1.000
Chile	**0.045***	0.114	62.2%	0.000	0.000	**0.935**	0.000	**0.995**	**0.997**	**0.999**	**2.18***	0.028	52.0%	0.100	0.000	1.000	0.180	1.003	1.003	1.003
Hungary	**0.050***	0.082	53.6%	0.000	0.000	**0.938**	0.000	**0.988**	**0.996**	**1.000**	0.580	0.001	52.2%	0.690	0.080	1.010	0.760	1.014	1.002	1.002
Czech	**0.023***	0.026	54.8%	0.000	0.000	**0.976**	0.000	**0.997**	**0.999**	1.001	-0.062	0.000	55.5%	0.940	0.030	1.011	0.820	1.009	**0.999**	**0.999**
Colombia	**0.040***	0.094	60.9%	0.000	0.000	**0.951**	0.000	**0.987**	**0.988**	**0.994**	**2.46***	0.038	55.0%	0.010	0.020	**0.990**	0.020	**1.000**	**0.987**	**0.995**
Peru	**0.006***	0.016	58.9%	0.000	0.000	**0.991**	0.000	**0.996**	**0.996**	**0.997**	**0.392****	0.007	55.6%	0.210	1.000	1.001	0.230	1.003	**0.998**	**0.993**
Indonesia	**0.014***	0.015	50.8%	0.000	0.050	**0.993**	0.030	1.003	1.003	1.004	0.010	0.000	50.6%	0.950	0.130	1.008	0.830	1.006	1.004	1.003
Thailand	**0.008***	0.017	55.9%	0.000	0.030	**0.987**	0.000	**0.995**	**0.998**	**0.996**	0.199	0.001	54.2%	0.510	0.000	1.007	0.250	1.005	**0.999**	**0.998**

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

Table 2g shows the results from the in-sample and out-of-sample exercises. OLS 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 2g 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.

	High Yield									
Countries	In-Sample					Out-of-Sample				
	OLS	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 2h – Results for In-Sample and Out-of-Sample analysis

Table 2h shows the results from the in-sample and out-of-sample exercises. OLS 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 2h 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										MLE									
Countries	In-Sample					Out-of-Sample					In-Sample					Out-of-Sample				
	OLS	R^2	HR	GC	GC Robust	1 Week	P-Value CW	2 Weeks	4 Weeks	8 Weeks	OLS	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**	**-0.019***	0.059	57.2%	0.000	0.020	**0.989**	0.000	**0.946**	**0.939**	**0.950**
Canada	**-0.018***	0.037	55.8%	0.060	0.140	**1.000**	0.015	**0.970**	**0.969**	**0.969**	**-0.011***	0.037	57.0%	0.010	0.300	**0.988**	0.030	**0.965**	**0.960**	**0.960**
Japan	**0.009****	0.008	47.5%	0.220	0.880	1.010	0.480	**0.994**	**0.997**	**1.000**	0.002	0.001	47.8%	0.600	1.000	1.008	0.870	1.003	1.003	1.002
New Zealand	**-0.026***	0.033	55.9%	0.060	0.160	**1.000**	0.090	**0.968**	**0.962**	**0.964**	**-0.016***	0.037	55.6%	0.000	0.090	**0.987**	0.000	**0.965**	**0.964**	**0.965**
Sweden	**-0.019***	0.026	53.4%	0.000	0.120	**0.991**	0.080	**0.979**	**0.981**	**0.988**	**-0.012***	0.030	55.2%	0.000	0.050	**0.984**	0.010	**0.971**	**0.973**	**0.977**
UK	**-0.016***	0.025	49.7%	0.060	0.300	**0.997**	0.100	**0.976**	**0.979**	**0.982**	**-0.009***	0.022	52.0%	0.020	0.200	**0.992**	0.030	**0.978**	**0.979**	**0.987**
Switzerland	**-0.008****	0.005	53.3%	0.110	0.500	1.000	0.210	**0.998**	**0.995**	**0.996**	**-0.006***	0.008	53.1%	0.030	0.160	**0.993**	0.010	**0.990**	**0.990**	**0.992**
Norway	**-0.023***	0.037	54.7%	0.000	0.000	**0.977**	0.020	**0.962**	**0.967**	**0.986**	**-0.013***	0.035	54.1%	0.000	0.000	**0.973**	0.000	**0.955**	**0.958**	**0.969**
Denmark	**-0.014***	0.019	52.8%	0.020	0.190	**0.994**	0.080	**0.987**	**0.986**	**0.991**	**-0.008***	0.020	51.9%	0.000	0.070	**0.985**	0.000	**0.978**	**0.979**	**0.983**
Israel	-0.006	0.005	52.8%	0.320	0.180	1.009	0.610	1.008	1.008	1.001	-0.004	0.007	52.7%	0.110	0.310	1.001	0.240	**0.999**	**0.997**	**0.998**
Brazil	**-0.030***	0.034	55.2%	0.050	0.020	1.003	0.110	**0.945**	**0.936**	**0.970**	**-0.018***	0.034	55.2%	0.000	0.120	**0.990**	0.020	**0.952**	**0.952**	**0.967**
South Africa	**-0.031***	0.033	54.2%	0.030	0.000	**0.991**	0.013	**0.949**	**0.942**	**0.956**	**-0.015***	0.020	52.7%	0.030	0.310	**0.991**	0.090	**0.968**	**0.964**	**0.970**
Turkey	**-0.029***	0.015	51.3%	0.050	0.000	1.010	0.220	**0.960**	**0.957**	**0.974**	**-0.021***	0.023	54.8%	0.000	0.000	**0.994**	0.090	**0.950**	**0.947**	**0.961**
Russia	-0.010	0.013	52.8%	0.070	0.030	1.002	0.390	1.001	1.002	1.005	**-0.009***	0.036	50.8%	0.000	0.000	**0.984**	0.000	**0.978**	**0.982**	**0.989**
South Korea	**-0.021***	0.040	55.8%	0.060	0.000	0.996	0.018	**0.956**	**0.953**	**0.962**	**-0.014***	0.054	56.3%	0.000	0.020	**0.976**	0.020	**0.956**	**0.959**	**0.966**
Mexico	**-0.021***	0.037	53.4%	0.110	0.010	1.004	0.200	**0.979**	**0.976**	**0.993**	**-0.013***	0.039	52.5%	0.030	0.030	**0.990**	0.030	**0.973**	**0.975**	**0.986**
Singapore	**-0.0064***	0.016	54.8%	0.030	0.150	**0.995**	0.050	**0.984**	**0.983**	**0.985**	**-0.004***	0.021	55.6%	0.000	0.080	**0.984**	0.000	**0.975**	**0.976**	**0.979**
Phillipines	-0.007	0.014	52.0%	0.000	0.110	**0.997**	0.060	**0.992**	**0.993**	**0.987**	**-0.004***	0.013	53.1%	0.010	0.240	**0.995**	0.030	**0.990**	**0.991**	**0.996**
Poland	**-0.022***	0.020	55.9%	0.130	0.080	1.007	0.340	**0.987**	**0.993**	**0.999**	**-0.016***	0.033	55.2%	0.010	0.030	**0.988**	0.010	**0.973**	**0.976**	**0.986**
Taiwan	**-0.006***	0.021	54.1%	0.020	0.030	**0.996**	0.050	**0.981**	**0.983**	**0.989**	**-0.004***	0.033	56.3%	0.000	0.000	**0.981**	0.000	**0.968**	**0.973**	**0.980**
Chile	**-0.029***	0.060	55.2%	0.000	0.000	**0.984**	0.020	**0.952**	**0.956**	**0.976**	**-0.015***	0.049	54.5%	0.000	0.000	**0.985**	0.010	**0.961**	**0.962**	**0.972**
Hungary	**-0.022***	0.021	54.7%	0.070	0.170	**0.999**	0.030	**0.985**	**0.988**	**0.994**	**-0.014***	0.024	52.7%	0.010	0.070	**0.990**	0.020	**0.978**	**0.979**	**0.984**
Czech	-0.012	0.009	54.5%	0.160	0.370	1.005	0.290	**0.997**	**0.997**	**1.000**	**-0.009***	0.013	54.2%	0.030	0.170	**0.995**	0.020	**0.988**	**0.987**	**0.991**
Colombia	**-0.022***	0.037	54.7%	0.000	0.000	**0.994**	0.040	**0.966**	**0.954**	**0.964**	**-0.012***	0.032	52.2%	0.000	0.060	**0.990**	0.020	**0.970**	**0.966**	**0.973**
Peru	**-0.005****	0.011	55.0%	0.070	0.440	1.003	0.180	**0.999**	1.003	1.010	**-0.003***	0.011	55.9%	0.030	0.140	**0.994**	0.020	**0.989**	**0.987**	**0.989**
Indonesia	**-0.021***	0.042	51.1%	0.000	0.040	**0.980**	0.020	**0.965**	**0.971**	**0.974**	**-0.012***	0.040	53.8%	0.000	0.040	**0.957**	0.000	**0.943**	**0.955**	**0.966**
Thailand	**-0.007***	0.017	56.3%	0.000	0.000	**0.994**	0.010	**0.989**	**0.989**	**0.990**	**-0.005***	0.023	54.5%	0.000	0.000	**0.986**	0.000	**0.976**	**0.977**	**0.980**

Figure 1a – Results of the Giacomini and Rossi (2010) instability test for REPO.

Figure 1a shows the results of the Giacomini and Rossi (2010) for the REPO. Results are reported for all countries in the sample.

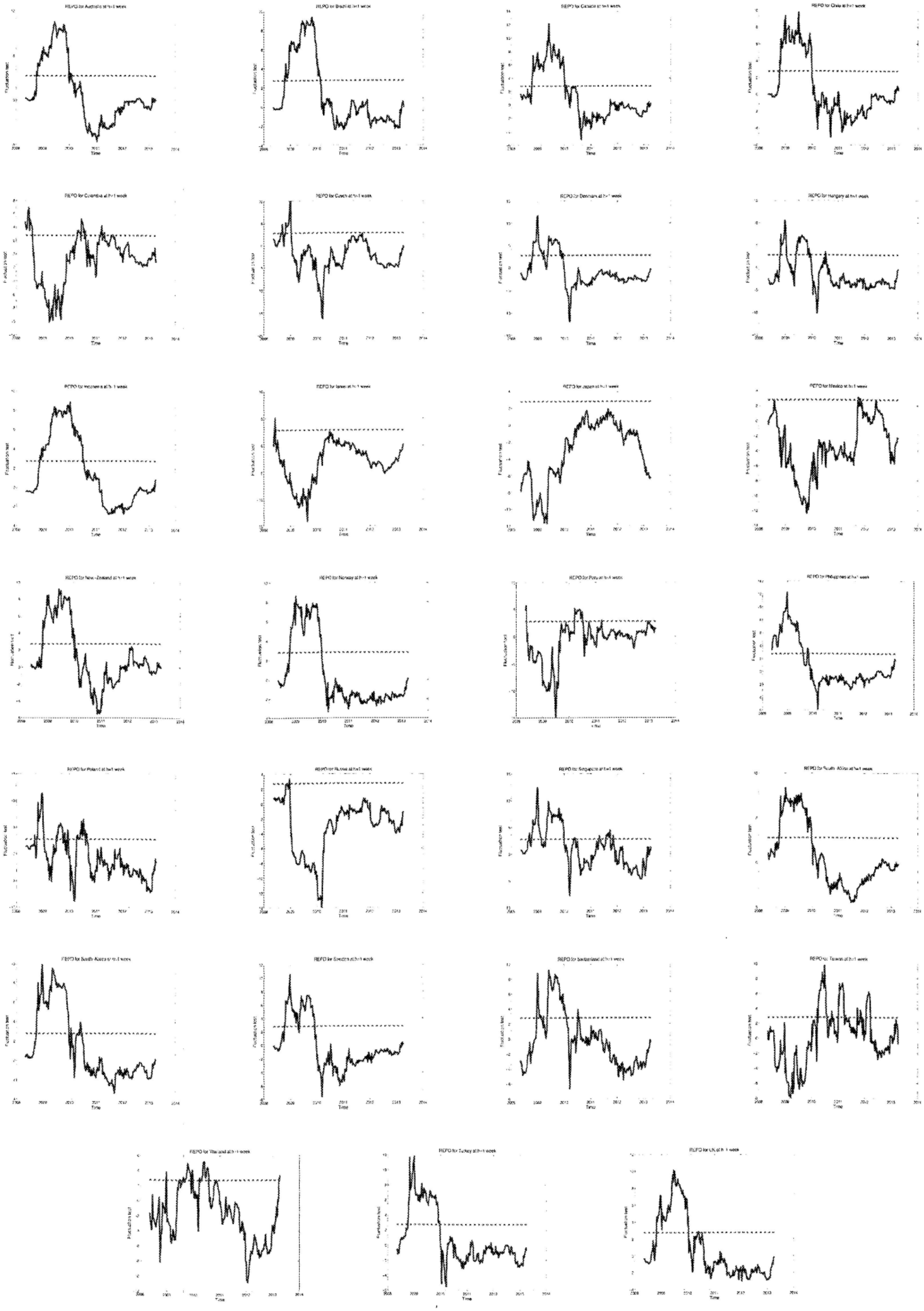


Figure 1b – Results of the Inoue and Rossi (2012) test for REPO.

Figure 1b shows the results of the Inoue and Rossi (2012) for the REPO. Results are reported for all countries in the sample.

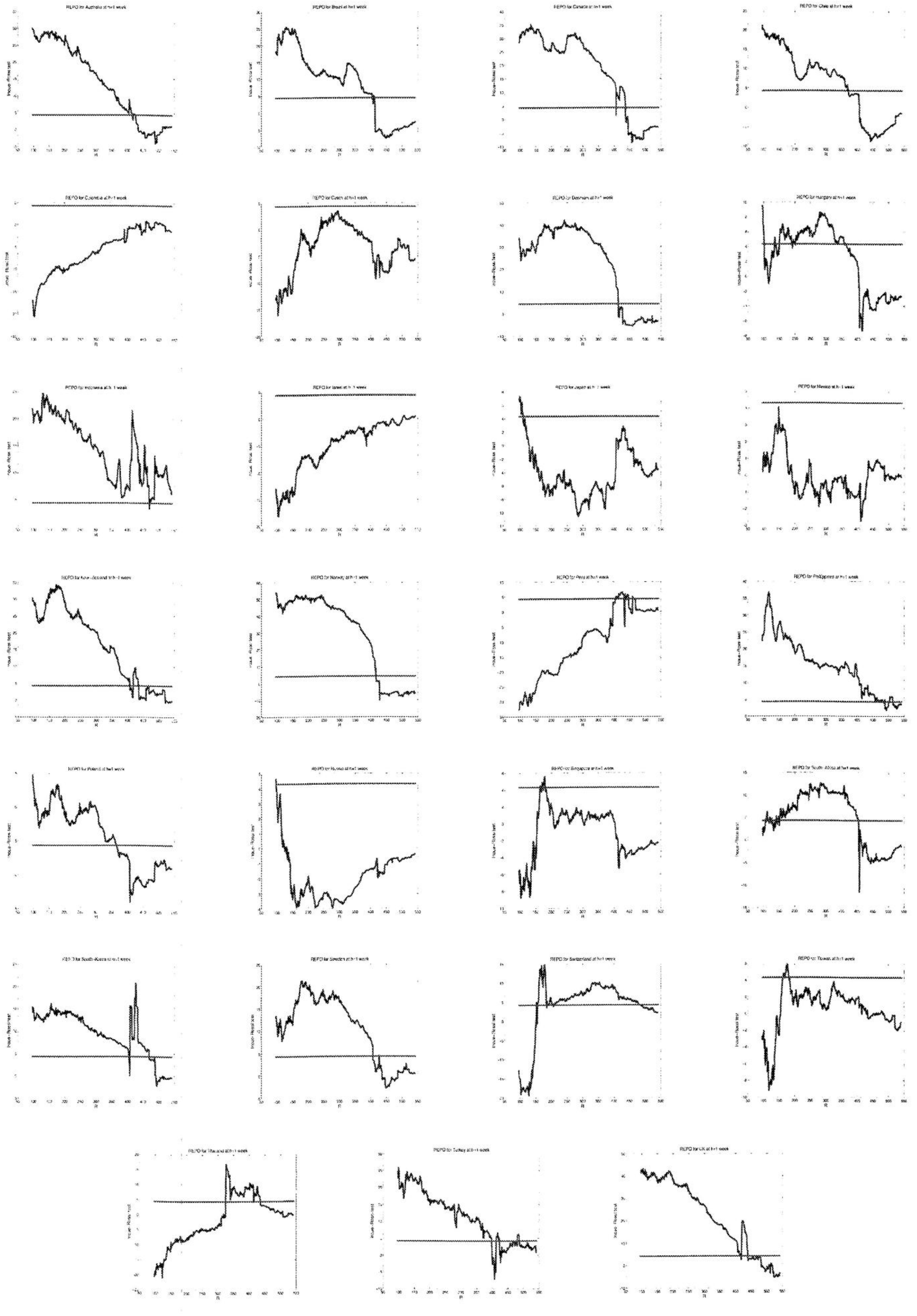


Figure 1c – Results of the Giacomini and Rossi (2010) instability test for BORROWINGS.

Figure 1c shows the results of the Giacomini and Rossi (2010) for BORROWINGS. Results are reported for all countries in the sample.

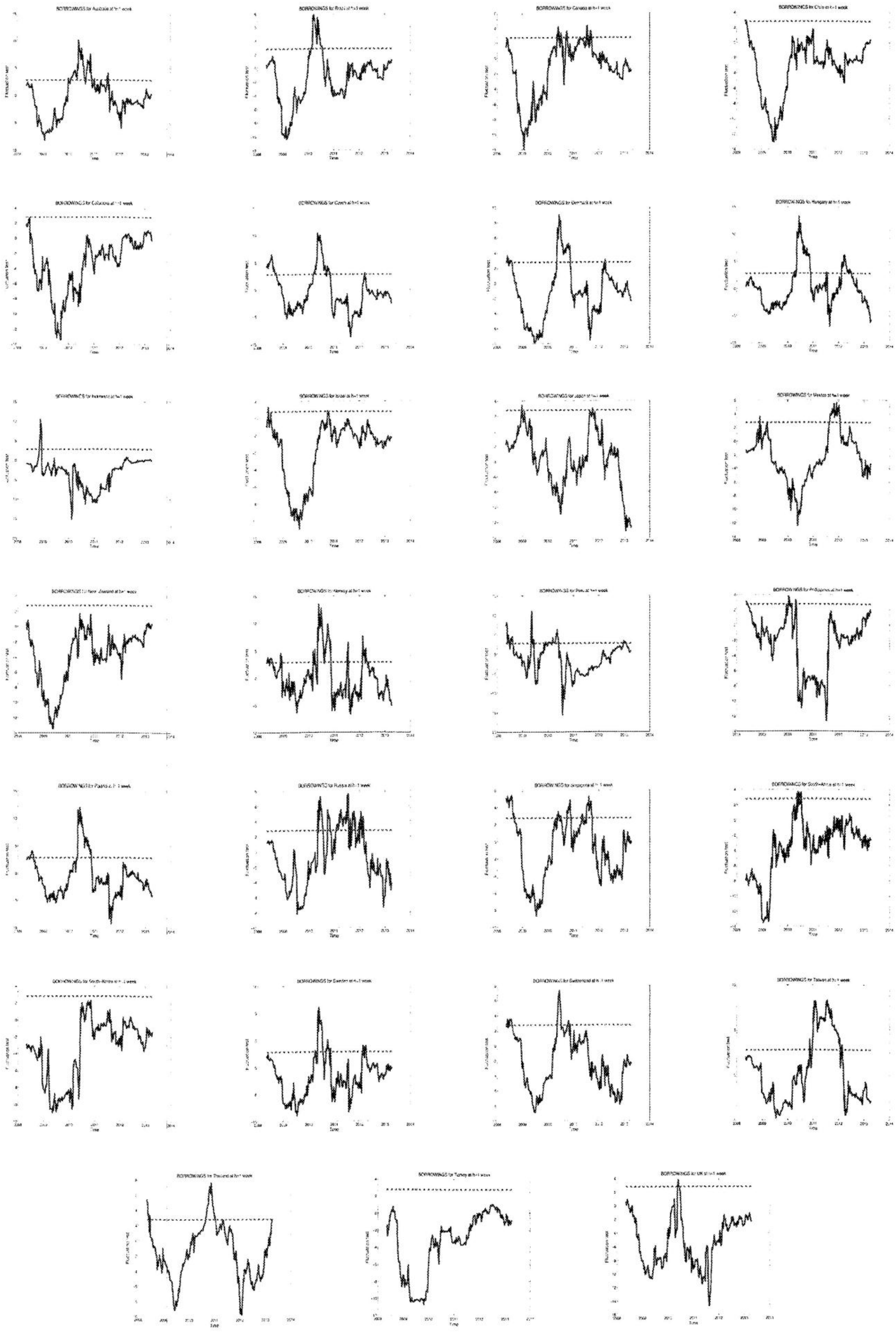


Figure 1d – Results of the Giacomini and Rossi (2010) instability test for M0.

Figure 1d shows the results of the Giacomini and Rossi (2010) for M0. Results are reported for all countries in the sample.

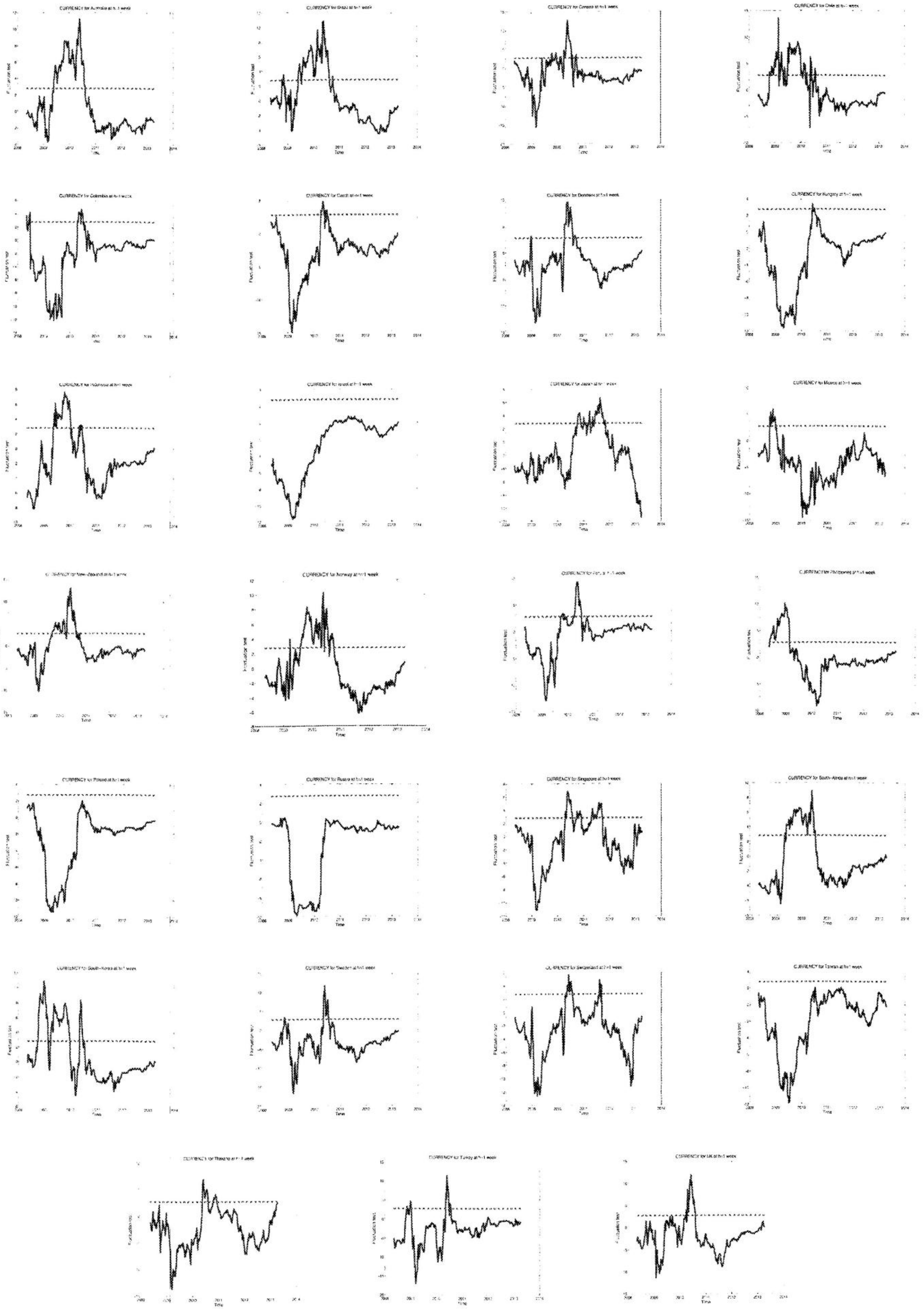


Figure 1e – Results of the Inoue and Rossi (2012) test for M0.

Figure 1e shows the results of the Inoue and Rossi (2012) for the M0. Results are reported for all countries in the sample.

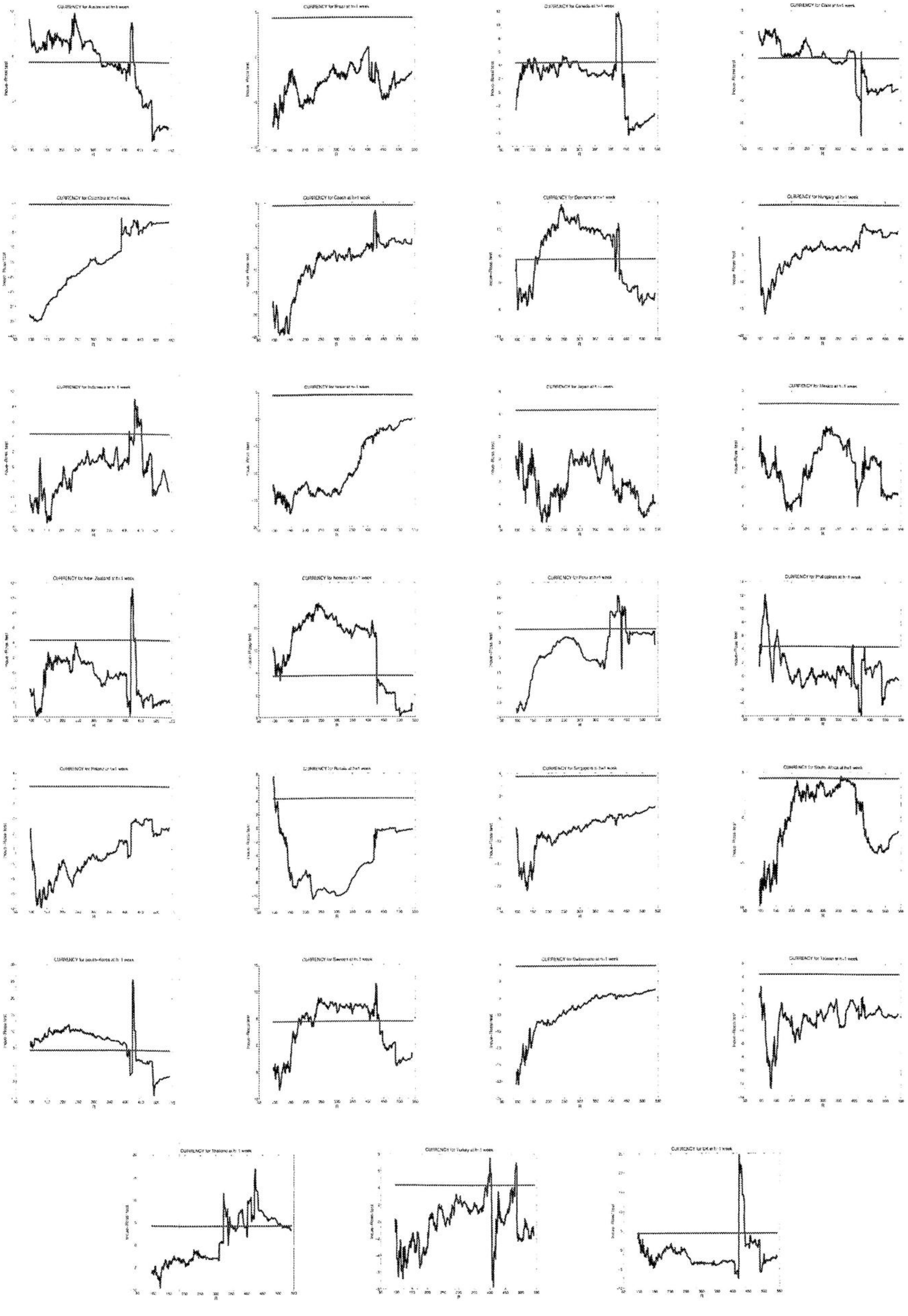


Figure 1f – Results of the Giacomini and Rossi (2010) instability test for T10Y.

Figure 1f shows the results of the Giacomini and Rossi (2010) for T10Y. Results are reported for all countries in the sample.

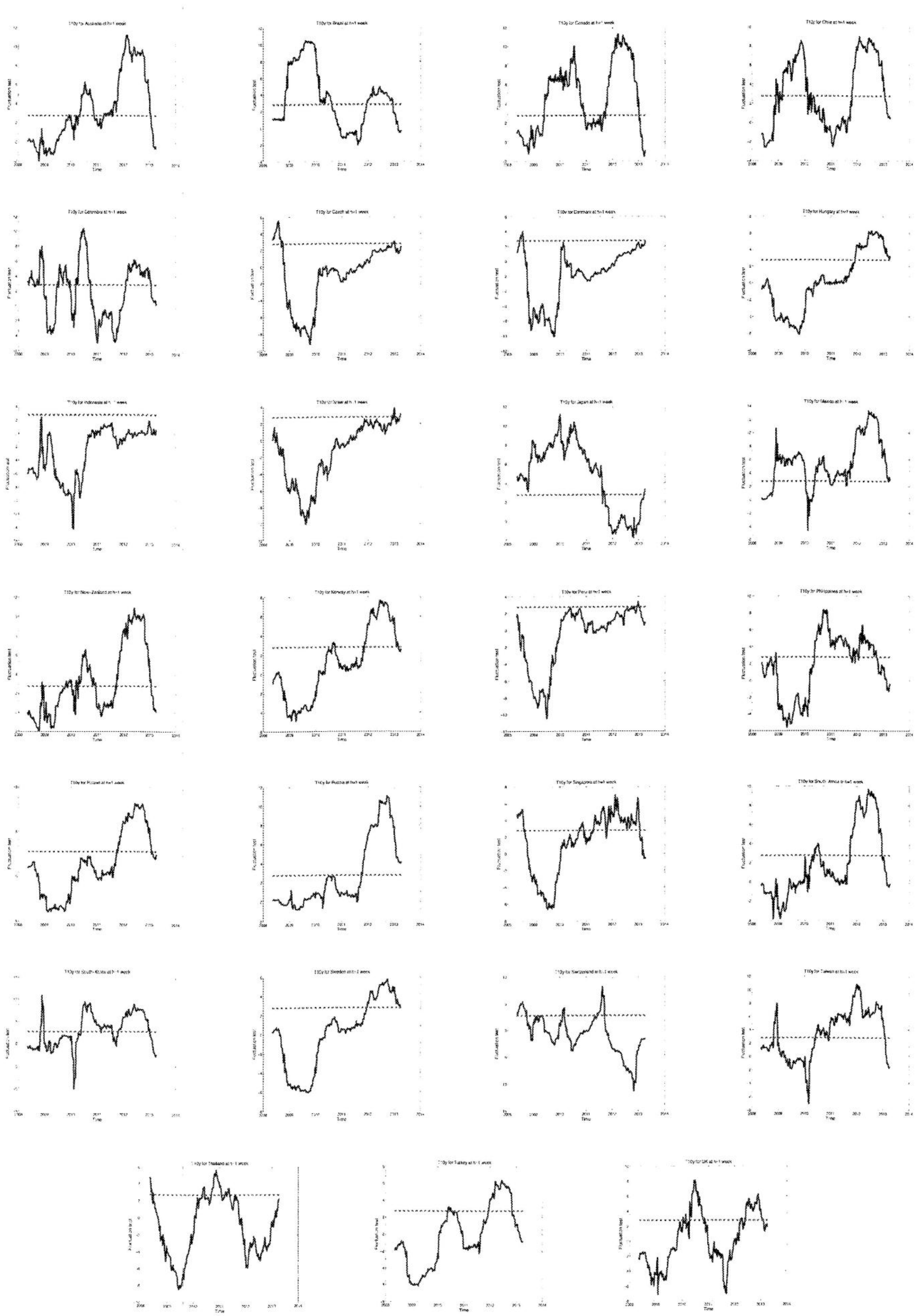


Figure 1g – Results of the Inoue and Rossi (2012) test for T10Y.

Figure 1g shows the results of the Inoue and Rossi (2012) for the T10Y. Results are reported for all countries in the sample.

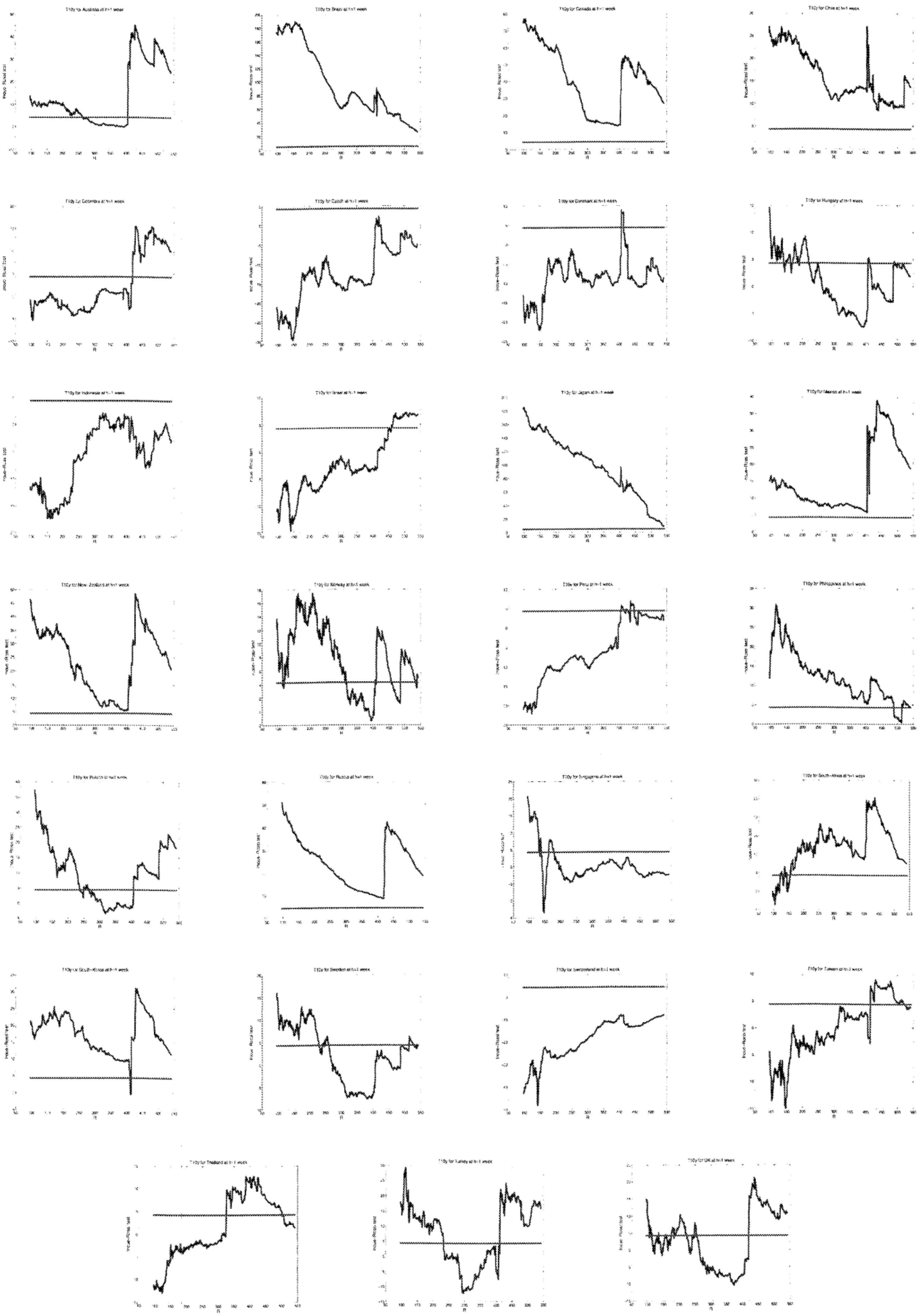


Figure 1h – Results of the Giacomini and Rossi (2010) instability test for VIX.

Figure 1h shows the results of the Giacomini and Rossi (2010) for VIX. Results are reported for all countries in the sample.

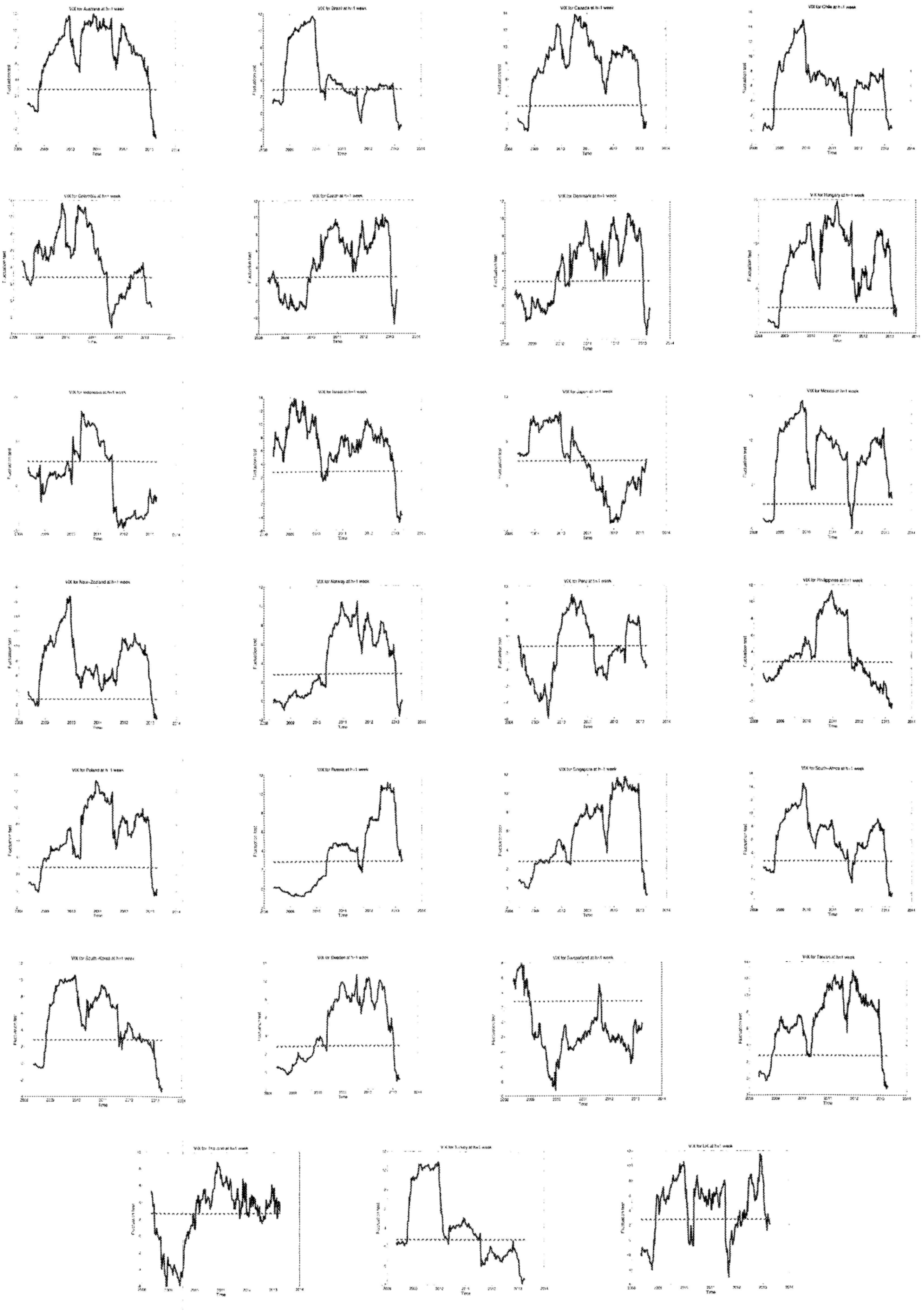
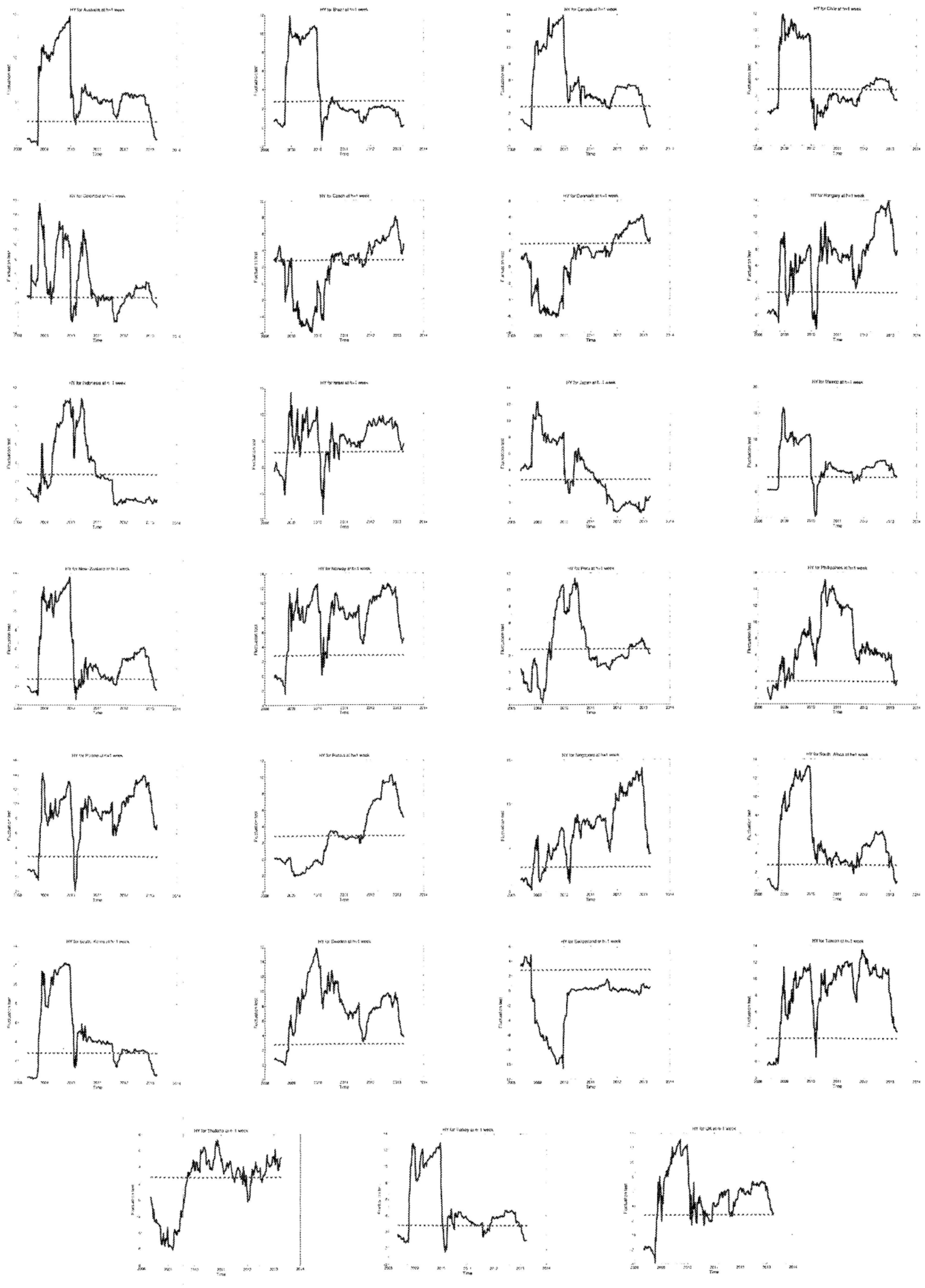


Figure 1i – Results of the Giacomini and Rossi (2010) instability test for HY.

Figure 1i shows the results of the Giacomini and Rossi (2010) for HY. Results are reported for all countries in the sample.



APPENDIX

Table A.1- Data Description

Table A.1 shows the data used throughout the text. Detrend stands for the use of detrend series using a HP-filter performed out-of-sample, as discussed by Adrian et al. (2010) to avoiding Look-ahead bias. Changes stands for changes in variables across two periods.

Variable	Description	Use	Source
COMM	The total outstanding stock of commercial paper	Detrend	FED
REPO	The total outstanding overnight repurchase agreements (REPO) of US financial intermediaries	Detrend	FED
DEP	Total resident deposits in the banking sector	Detrend	
SPREAD	The spread between domestic deposit rate for deposits with a maturity of up to one year and the 6-month interbank interest rate	Changes	FED
BORROW	Total loans of financial institutions from other financial intermediaries	Detrend	FED
CREDIT	Total bank credit to the non-financial private sector	Detrend	FED
M0	Notes and coins in circulation - Currency	Detrend	FED
M1	M1 Monetary Aggregate	Detrend	FED
M2	M2 Monetary Aggregate	Detrend	FED
T10Y	10-year Treasury Bond Yield	Changes	FED
VIX	The implied volatility of S&P 500 index options	Changes	CBOE
TED	The difference between the three-month LIBOR and the three-month T-bill interest rate	Changes	Datastream
HY	The spread between high-yield bonds (non-investment grade) and investment-grade corporate bonds	Changes	FED St. Louis
ML	Merrill-Lynch Global Liquidity Index	Changes	Bloomberg
MLE	Merrill-Lynch Liquidity Index for Emerging Markets	Changes	Bloomberg