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ABSTRACT

The level of the (log of) the exchange rate seems to have strong forecasting power for dollar exchange rates against major currencies post-2000 at medium- to long-run horizons of 12-, 36- and 60-months. We find that this is true using conventional asymptotic statistics correcting for serial correlation biases. But correcting for small-sample bias using simulation methods, we find little evidence to reject a random walk. This small sample bias arises because of near-spurious correlation when the predictor variable is persistent and the horizon for exchange rate forecasts is long. Similar problems of spurious correlation may arise when other persistent variables are used to forecast changes in the exchange rate. We find, in fact, using asymptotic statistics, the level of the exchange rate provides better forecasts than economic measures of "global risk", and the measures of global risk do not improve the (possibly spurious) forecasting power of the level of the exchange rate.

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1. Introduction

The "gold standard" for testing exchange rate models is evidence of forecasts of changes in the exchange rate that produce a lower mean-squared error than the random walk prediction of no change. For many years, the literature has consistently found that macroeconomic variables are not helpful in forecasting the U.S. dollar exchange rate change.[1] However, in recent years, many new studies have found evidence of predictability, particularly at medium-run horizons of 1- to 5-years, especially using measures of global uncertainty to help forecast the dollar. The exchange rates of the U.S. dollar in the 21st century relative to the other G10 currencies appears to be a borderline stationary random variable, but very persistent.[2] This behavior of these exchange rates, presented in Figure 1, presents difficulties in assessing the power of economic models to forecast the dollar.

If dollar exchange rates truly are stationary, then changes in the exchange rate should be easily forecastable – "beating" the random walk is not difficult. In fact, we find that the level of the log of the exchange rate itself is a powerful predictor of changes in the exchange rate using the same standards for measuring success as the literature has used. (Hereinafter, we will use simply "exchange rate" to refer to the "log of the exchange rate.")

However, it is easy to make mistaken inference in assessing forecasts at these horizons, as a large literature has established, because of problems in serial correlation of forecast errors, small-sample bias in parameter estimates and in establishing the correct statistical distribution of test statistics when the exchange rate has a unit root under the null hypothesis (of a random walk) but is stationary or cointegrated with other economic variables under the alternative. These problems come into play in forecasting the dollar at medium horizons because the dollar is persistent but "borderline" stationary. These G10 exchange rates are highly serially correlated, but, as we shall show, it is unclear if they are the outcome of a unit root process. The R^2 and asymptotic *t*-statistics in long-horizon regressions are very high, and forecasts based on the level of the log exchange rate performs well out-of-sample against the random walk using asymptotic statistics. On the other hand, simulation-based tests indicate we may not be able to reject the simple hypothesis that the exchange rates follow a random walk at standard significance levels.

[1] See the surveys and syntheses in Cheung et al. (2005, 2019).

[2] The non-dollar G10 currencies are the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), the euro (EUR), U.K. pound sterling (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SWE).

These findings pose a challenge for exchange rate forecasts based on economic models: We find using standard asymptotic statistics that many of these variables do not forecast better than the level of the exchange rate itself, and do not improve on the forecast made by the level of the exchange rate, while keeping in mind that the seeming forecast power of the level of the exchange rate is itself dubious. This leads us to conclude that the small-sample properties of forecasts based on economic variables must be carefully investigated.

Our approach is first to examine the univariate properties of the nominal exchange rate. As is typical in the literature, we look at the statistical inference from in-sample and out-of-sample medium-horizon forecasts that adjust for the serial correlation in forecast errors, but not for the small-sample properties of these statistics. We compare the forecasting power of the level of the exchange rate to forecasts that use measures of global risk.

In-sample medium-horizon (12-month, 36-month and 60-month) forecasts of the change in the exchange rate produce eye-popping *R*-squared values – that is, eye-popping if the small-sample properties of such tests are ignored. At the 60-month horizon, the *R*-squared of the forecast of the change in the dollar exchange rates, in which only the level of the exchange rate is used to forecast future changes, is greater than 0.7 for six of the ten exchange rates, and greater than 0.6 for all but one of the currencies. These regressions produce highly statistically significant evidence of forecastability when using asymptotic statistics, even when we carefully correct for serial correlation in the forecast errors and when we allow for non-standard distribution of the parameters under the null of a random walk.

The literature on exchange rates pays special attention to out-of-sample forecasting power. Studies often compare the forecasting power of an economic model to that of a random walk using the Clark and West (2006) statistic for assessing forecasting power of nested models. While the small-sample biases in the "long-horizon" regressions described in the previous paragraph have been examined in depth, less attention has been paid to the problems with the Clark-West tests for medium-horizon forecasts. We find that tests of out-of-sample forecasting power of the level of the exchange rate based on rolling regressions produce large Clark-West statistics that, under the asymptotic distribution (and corrected for serial correlation), are very highly significant for medium-horizon forecasts.

We also note that rolling regressions often generate high values for *t*-statistics and R^2 in some sub-samples. We demonstrate that the level of the exchange rate can produce very high measures of fit for the subsequent change in the exchange rate over some subsamples in our data for U.S. dollar exchange rates.

Yet when we use simulation methods to correct for short-sample bias, we find that the in-sample forecasting power of the univariate model is not generally significantly better than that of a simple random walk at all the forecast horizons. However, we do find that when estimated as a panel, the in-sample forecasting power at the 60-month horizon is marginally significant by one measure, with a p-value of 0.05, even though the small-sample distribution of the test statistics is vastly different than the asymptotic distribution. Our simulation methods show that the forecast based on the level of the exchange rate does not significantly outperform the random walk in out-of-sample forecasting exercises. And, the very high levels of goodness of fit that we find in rolling regressions are within the bounds of what we would find if the exchange rate were not predictable at all. In summary, while the level of the exchange rate appears to have great forecasting power using conventional statistics, we cannot confidently say that the model beats a random walk.

These findings have implications for the literature that has found that measures of global risk are useful in forecasting dollar exchange rates at medium- and long-horizons. First, whether or not the exchange rate has a unit root, our simulations indicate that the bias in inference from medium- and long-run forecasts of exchange rates can be very large when the predictor variable is persistent. It is imperative that researchers consider small-sample bias. Second, one might take a stand and assume that the nominal exchange rate is indeed stationary, since a failure to reject a random walk does not imply the null is true. Also, in some cases, the rejection is marginal. But we show those global risk measures are apparently no better at forecasting future changes in the exchange rate than the level of the exchange rate itself, and do not provide additional forecasting power to that provided by the level of the exchange rate. If the exchange rate is stationary, an interesting question is whether an economic model can improve on the forecast made only from the level of the exchange rate.

These comparisons between the forecasting power of the global risk variables and the level of the exchange rate are made for in-sample forecasts and out-of-sample forecasting power, and we also compare the goodness of fit of the models over subsamples. We do this for a dozen measures of global risk, and we also make the comparison of the forecasting power of the nominal exchange rate to that of the real exchange rate.

We do not try to directly assess the small sample properties of forecasts of exchange rates based on economic variables. We are making the indirect point that if the forecasting power using the level of the exchange rate is questionable, then the literature ought to be investing more effort in assessing the small sample properties of forecasts made using global risk and other variables. Why do we not take this approach directly? The answer is that this task should be approached on a case-by-case basis for each forecasting model. When the forecasting variable is the level of the exchange rate, it is straightforward to construct the distribution of the exchange rate and the forecasting variable under the null hypothesis of a random walk. [3] As the literature has shown, it is not so easy when the forecasts are made using some other variable, call it x_t. How should x_t be modeled when the null is that $s_{t+j} - s_t$ is unforecastable? We could model x_t as being independent of s_t, but more plausibly innovations in x_t are correlated with innovations in s_t, Measuring this correlation requires a model for innovations in x_t.

Moreover, there is the question of whether x_t is stationary. For example, we find that the linearly detrended value of the log S&P 500 index has some in-sample forecasting power for changes in the exchange rate. But if this variable actually has a unit root, then our forecasting models, based on regressions of $s_{t+j} - s_t$ on x_t are unbalanced. If we treat x_t as an I(1) variable, we not only need to consider whether or not its innovations are correlated with innovations in s_t under the null hypothesis, but also whether or not it is cointegrated with s_t under the null and/or the alternative hypotheses.[4] We do offer one example of a possible assessment of small-sample properties at the end of section 3 and we find weak evidence of forecasting power of x_t, but that analysis not a one-size-fits-all solution.

Our purpose here is not to criticize any specific study that has demonstrated empirical support for an exchange rate model, but instead to suggest that extra care be given in assessing the

[3] There are also analytic corrections for small-sample bias, but we rely on simulation methods because they are easy to implement and the properties of such simulations are well established in the univariate case under the null of a random walk.

[4] That is, there may plausibly be cointegration under both the null and the alternative, under neither the null nor the alternative, or under the alternative but not the null.

goodness of fit of in-sample medium-run forecasts and the out-of-sample forecasting power of models over medium horizons.[5]

In section 2, we examine the forecasting power for changes in the exchange rate of the level of the exchange rate and of measures of global risk, using standard asymptotic statistics (corrected for serial correlation.) We also look at the forecasting power of global risk variables and the real exchange rate. In section 3, we re-examine the univariate exchange rate model using simulation methods. We offer some conclusions and suggestions in the final section.

2. Dollar exchange rate forecasts

The exchange rate, denoted as s_t, is the U.S. dollar price of a foreign currency. For the whole empirical exercise, we use exchange rates sample from January 1999 to March 2020. The data appendix reports the data sources and sample period for other relevant macro variables used.

2.a. Medium- and long-horizon forecasts

We begin by assessing the fit of the *h*-period ahead forecasting equation using asymptotic test statistics:

$$(1) \qquad s_{t+h} - s_t = \alpha_h + \beta_h s_t + u_{t+h}$$

for forecasts horizons of $h = 1, 12, 36, 60$ months. Table 1 presents the OLS estimates of β_h with Newey-West standard errors.[6] The forecasting power of the level of the exchange rate is of interest in part because if the level of the exchange rate can forecast future changes in the exchange rate, it may be evidence that the exchange rate is stationary.[7] Medium- and long-horizon forecasting power might provide evidence that is not apparent in standard tests of a unit root which often rely

[5] Some recent papers are Adrian and Xie (2020), Ca'Zorzi and Rubaszek (2020), Darvas and Schepp (2020), Eichenbaum et al. (2020), Evans (2020), Jiang et al. (2019), Lilley et al. (2019), Lustig et al. (2016), Liu and Shaliastovich (2017) and Ma and Zhang (2020).

[6] We use *h*-1 lags for the Newey-West statistics. However, our findings are not very sensitive to the choice of lags as we find very similar results using 5 lags only for all the forecast horizons. See the extended notes on estimation for each table for more details.

[7] Lustig, et al. (2016), for example, have claimed recently that dollar exchange rates are stationary.

on the variable following a linear and low-order autoregressive or moving average process under the null and the alternative.

Test statistics for the null of $\beta_h = 0$ have non-standard distributions because the exchange rate has a unit root under the null. We use statistics based on the asymptotic distribution. employing the Phillips and Perron (1988) test, allowing serial correlation of order *h*-1. In section 3, we use simulation methods to assess the distributions, and we find that the inference based on the simulated distributions is dramatically different than the asymptotic distribution. Similar problems arise when using economic variables to forecast changes in the exchange rate, and section 3 cites some of the voluminous literature on this point.

s_t is not a good predictor of one-month ahead changes in the exchange rate. β_1 is insignificantly different from zero for all the currencies. The adjusted R^2 values are all less than 0.01. We also estimate equation (1) in a panel form with country (*i*) fixed effect:

$$s_{i,t+h} - s_{i,t} = \alpha_{i,h} + \beta_h s_t + u_{i,t+h}$$

The bottom row of Table 1 presents estimates with Driscoll and Kraay (1998) standard errors using *h*-1 lags. The slope coefficient is not significant and the "within" R^2 is only 0.003, so the evidence of predictive power at the short horizon is very weak.[8]

The picture changes substantially at the 12-, 36-, and 60-month horizons. At all these horizons, the level of the exchange rate is significant at the one percent level for all the currencies. The table also presents two measures of the overall (rather than currency-by-currency) forecasting power. In one, we calculate the simple average of the exchange rates (labeled SA), and find significant explanatory power of s_t for $s_{t+12} - s_t$. In the second, we estimate a fixed-effect panel and calculate standard errors using the Driskill-Kraay method, and again find the slope is statistically significant. The R^2 values for these two regressions at the 12-month horizon are both 0.11.

Even more striking is the seeming forecasting power for the 36-month and 60-month changes in the exchange rate. The R^2 values are very high. At the 36-month horizon, most of the R^2 levels are above 0.4 and some are above 0.5. At 60 months, the R^2 for example, is 0.78 for the

[8] As the extended notes detail, we use the unit root tests for panels of Choi (2001) to draw statistical inference.

dollar/euro rate, 0.76 for the simple average (SA) exchange rate, and 0.66 for the within R^2 in the panel regression.

All these regressions indicate that the level of the exchange rate has strong and statistically significant predictive power for changes in the exchange rate over medium horizons. However, there are well-known problems arising from small-sample bias especially at longer horizons. We shall return to these issues in section 3.

2.b Out-of-Sample Forecasts

The previous sub-section examined the "in-sample" forecasting power of the level of the exchange rate. In recent years, the "gold standard" for evaluating the ability of a model to forecast is the "out-of-sample" forecasting criterion.

Specifically, the methodology that is widely adopted is to estimate equation (1) over sub-samples of the data using rolling regressions (i.e., regressions with fixed sample sizes.) Here we use sub-sample sizes of five years. We estimate (1) over the first five years of data, and then use the estimated parameters to make forecasts 1-month, 12-months, 36-months and 60-months ahead. We then drop the first observation in the sample and add the 61st observation, and re-estimate equation, and produce one more forecast at each horizon. We continue this process until the data is exhausted.

We use the root mean-squared error as a measure of fit for the forecasts at each horizon, $s_{t+h} - s_t$, for $h = 1, 12, 36, 60$. The literature has then used the random walk forecast of no change in the exchange rate as the basis of comparison. This criterion stems from the seminal work of Meese and Rogoff (1983) that use the forecast of "no change" in the exchange rate to evaluate exchange rate models of the 1970s.[9] The random walk, with no drift, is nested in the model of equation (1) when $\alpha_h = 0$ and $\beta_h = 0$.[10] The Clark and West (2006) statistic is commonly used to evaluate the out-of-sample forecasting power of exchange rate models relative to a nested model.[11]

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[9] Meese and Rogoff (1983) actually looked at the out-of-sample fit of the models compared to the random walk, rather than using the models to make actual out-of-sample forecasts.

[10] Here, and throughout the rest of the paper, we take the null hypothesis to be the random walk with no drift, as is typical in the literature. However, we have replicated all tests under the assumption of a null of a random walk with non-zero drift equal to the mean drift in the sample, and in no case do our conclusions change. This partly is reflective of the fact that for most of the exchange rates, the mean drift in this sample is quite small.

[11] We use a Newey-West correction for serial correlation.

The Clark-West statistic compares the mean squared errors of two nested models and accounts for the larger estimation error of the larger model. A bigger positive Clark and West statistic indicates the larger model performs better than the nested model.

The Clark-West statistics reported in Table 2 are striking. At the one-month forecasting horizon, the forecasting equation (1) does not produce significantly better forecasts than the random walk, but for the 12-month, 36-month, and 60-month forecasts, the model's predictions are significantly better for all currencies as well as for the simple average of the exchange rates and for the panel. At the twelve-month horizon, the Clark-West statistic is significant at the five-percent level in all but one case; at the 36-month horizon it is significant at the five percent level for all exchange rates and at the one percent level for most; and, at the 60-month horizon the significance level is one percent for all but two currencies.

While it appears that model (1) can provide superior forecasts to the random walk, again we must be aware of the small-sample bias, which we address in section 3.

2.c Rolling Regressions

Next, we make use of the same rolling regressions discussed in the previous sub-section to make an observation about the fit of regressions over sub-samples. Most exchange rate studies present regression results over various sub-samples, even in some cases estimating rolling regressions, and then noting the very good fit of the model over certain periods.[12] Table 3 displays the sample distribution of adjusted R^2 values from our rolling regressions.

The R^2 for the 1-period ahead forecasting regression is sometimes large, reaching a maximum of 0.20 in at least one five-year period for seven of the nine currencies. However, consistent with the results we have already presented, usually the fit of the forecasting regression at this horizon is poor and not at all impressive.

However, at the 12-month, 36-month and 60-month horizons, the forecasting equation has a very tight fit over some sub-samples. In the case of the 12-month forecasts, the adjusted R^2 reaches at least a value of 0.75 in one sub-sample for all nine of the exchange rates for the individual currencies. In at least 10 percent of the sub-sample regressions, the R^2 is as high as 0.64

[12] Lilley, et al. (2019) is an example of a paper that estimates a model over many sub-samples with rolling regressions and notes the close fit over some samples.

for all nine. At the 36-month horizon, there is at least one sub-sample that has an R^2 as high as 0.80 for all the currencies, and for half of them, there is a period in which the R^2 rises to 0.90 With the 60-month forecasting equation, all nine of the currencies show an adjusted R^2 of at least 0.77 during one five-year sub-sample, and for several, the R^2 in some sub-samples range well over 0.90. Moreover, in 25% of the sub-samples for each currency, the R^2 value is as high as 0.60 for all nine exchange rates, and in some cases the 75th percentile of R^2 values is much higher (including 0.94 for the dollar/Swiss franc.)

One might be tempted to conclude from this that the simple forecasting equation (1) is a sure winner over at least some time periods in the 21st century. However, there is always the temptation with any pair of variables to look over sub-samples and find correlation. In section 3, we evaluate the extent to which these high correlations are spurious.

2.d Forecasting using measures of global risk

As we have seen, the apparent forecasting power of the level of the exchange rate is quite strong. In this section, we will compare its forecasting power to that of various measures of global risk. Recent studies have linked the dollar's behavior to global risk, noting that the U.S. dollar strengthens during periods of global stress. Our purpose in making these comparisons is not to set up a horse race between the global risk measures and the level of the exchange rate for which makes better forecasts. We only want to note that the global risk variables do not appear to have clearly stronger forecasting power than the level of the exchange rate, so our concerns about the small-sample properties of forecasting equations based on the level of the exchange rate ought to also lead researchers to have similar concerns about forecasting equations based on measures of global risk.[13]

We shall see that while, at medium and longer horizons, forecasts based on the measures of global risk can often "beat" the random walk, they are less successful at beating the forecasts based on s_t. We call this a "preliminary look" because we use standard asymptotic statistics to perform these tests, while a more rigorous testing procedure would consider small-sample bias (which we do not undertake for reasons outlined above in the introductory section.)

[13] Many of these measures are highly persistent, see Appendix Table 2 for the summary statistics.

We examine the forecasting power of 12 macro variables that are used in the recent literature to explain or predict exchange rate movements. These variables include 1) the "US Treasury Premium", which is the one-year covered interest parity deviation of government yield between US and a foreign country. 2) the "MAR global factor" is the global factor that is extracted from a dynamic factor model of a wide range of world asset price series. This is constructed by Miranda-Agrippino and Rey (2020). 3) the "GZ spread" is a simple un-weighted cross-sectional average of US corporate non-financial credit spreads, which is obtained from Gilchrist and Zakrajšek (2012). 4) the linearly detrended "log of S&P500 Index". 5) the "log of VIX Index", which measures the equity market's expectation of 30-day forward-looking volatility. 6) the "Term spread (5y-FF)" is difference between 5-year US Treasury yield and overnight Fed Fund rate. 7) the "Term spread (10y-2y)" is yield difference between 10-year US Treasury and 2-year US Treasury. 8) "TED" is the yield difference between US dollar LIBOR rate and US Treasury at 3-month horizon. 9) the "Intermediary capital ratio" is the market capitalization-weighted average of New York Fed primary dealers' equity to asset ratio, which is constructed by He et al (2017). 10) the "Intermediary weighted return" is the market capitalization-weighted equity return of the holding companies of the primary dealer of New York Fed, which is constructed by He et al (2017). 11) "Repo" is the linearly detrended log of Overnight Repo outstanding of the primary dealers. 12) "Commercial Paper" is the linearly detrended log of Financial Commercial Paper outstanding of the primary dealers. [14] The data appendix provides the data source, the sample period, and the summary statistics of these macro variables.[15]

We examine forecasts from four models – a model using both the level of the exchange rate and the global risk variable to make forecasts, models using only the level of the exchange rate or only the global economic variable, and the random walk model. These models can be summarized in these four equations:

[14] US Treasury Premium is used in Du et al (2018), Engel and Wu (2020) and Jiang et al (2019). MAR global factor and GZ spread are used in Lilley et al (2020). SP500 Index is used Lilley and Rinaldi (2020). VIX is used in Brunnermeier et al (2009), Habib and Stracca (2012), Sarno et al (2012), Bussière et al (2018), Husted et al (2018) and Kalemli-Özcan and Varela (2019). Term structure is used in Chen and Tsang (2013). TED is used in Cheung et al (2019). Intermediary capital ratio is used in Fang and Liu (2020) and is the core friction is Gabaix Maggiori (2015). Intermediary weighted return is used in Lilley et al (2020). Repo and commercial paper are used in Adrian, Etula, Shin (2015)

[15] When detrending the S&P500 Index, Outstanding Repo and Financial commercial papers, for in sample forecasting, we detrended the variable using the whole sample. For out-of-sample forecasting, we detrended the variable using the 60 observations within the window.

(2) $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{SS} s_t + u_{t+h}$

(3) $s_{t+h} - s_t = \alpha + \beta^{S} s_t + u_{t+h}$.

(4) $s_{t+h} - s_t = \alpha + \beta^{X} X_t + u_{t+h}$

(5) $s_{t+h} - s_t = u_{t+h}$.[16]

We consider forecasts horizons of $h = 1, 12, 36, 60$ months.

Within-sample forecasts

Table 4 summarizes the regression results for the simple average of the dollar exchange rate of the G10 currencies. The left-most four columns of statistics in Table 4 directly compare the univariate in-sample forecasting power of the nominal exchange rate to the economic variables (model (3) and model (4).) The straightforward conclusion is that the sample forecasting power of the level of the exchange rate is greater than for any of the economic variables. The goodness of fit measure is higher – usually much higher – for the forecast horizons of 12-, 36- and 60-months. Neither the level of the exchange rate nor the economic variables demonstrate forecasting power at the 1-month horizon.[17]

The right-most two columns report the forecasting equation for the average exchange rate based on an OLS regression in which both the current exchange rate and one of the measures of global risk are included as regressors (model (2)). At the one-month horizon, as was the case in the univariate in-sample forecasts, the level of the exchange rate is not statistically significant. There is some evidence that some of the measures of global risk are helpful in forecasting at the one-month horizon. The detrended S&P 500 level, the Repo outstanding for primary dealers and the 10-year to 2-year U.S. term spread are significant at the 5 percent level and intermediary leverage at the 10 percent level.[18]

At the medium horizons of 12-, 36- and 60-months, the exchange rate is always statistically significant at the one percent level when any other economic variable is included in the regression. There is less evidence of forecasting power for the measures of global risk. The log of the repo

[16] As we have noted previously, the findings are not changed if we include an intercept in this equation.
[17] An exception is that the detrended log S&P 500 shows significant forecast power at the one-month horizon.
[18] The inference on significance is based on the t-distribution for the economic variables, and on the Phillips-Perron statistic for the exchange rate.

rate is a strong predictor of exchange rate changes at all the horizons, in that it is statistically significant at the one percent level. Other variables show forecasting power at some horizons but not others. For example, the detrended S&P 500 is significant at the 12-month and 36-month horizons, but not at the 60-month, and the GZ spread at the 12- and 35-months horizons. Intermediary leverage is highly significant in the one-year forecasts, but not so for longer horizons. On the other hand, commercial paper is significant at the longer horizons (36- and 60-month) but not at the shorter horizons. Some other variables show up as significant at only one of the horizons (e.g., the TED spread at the 60-month horizon.)

An interesting aspect of these bivariate regressions is that in many cases, global risk variables that are not statistically significant in univariate forecasts become strongly significant in the bivariate regressions. For example, at the 60-month horizon, three variables are significant at the one percent level – the TED spread, primary dealer repo, and commercial paper – that are not significant in the univariate regression. On the other hand, 10-year-2-year U.S. term spread and the measure of intermediary leverage are significant in the univariate regression but not in the bivariate regression at the 60-month horizon. If the nominal exchange rate is stationary, this suggests that the univariate regressions are misspecified and that the current exchange rate should be included along with the measure of global uncertainty.

Table 5 summarizes the findings for the univariate and bivariate regressions for the nine individual currencies. We count the number of currencies that have a significant slope coefficient at 5 percent significance level. The findings are similar to the conclusions from the average exchange rate. Some of the economic variables are significant at the 5 percent level in univariate exchange rate regressions at all horizons, though none is significant for all of the exchange rates.[19] This can be compared to Table 1, which shows the level of the exchange rate is significant at the one percent level for all of the horizons greater than or equal to 12 months. In the bivariate regressions, the exchange rate continues to be significant at the 5 percent level at all horizons according to Table 4b.[20] In these regressions, different measures of global risk turn out to be significant for some of the exchange rates at some of the horizons. Primary dealer repo is

[19] Intermediary leverage is significant for all nine currencies at the 60-month horizon the S&P 500 return is significant for all nine of the currencies at the 12-month horizon, and the GZ spread is significant at the 36-month horizon for eight currencies.

[20] At all of the horizons greater than or equal to 12 months, the exchange rate is a significant predictor for all of the currencies, except at the 12-month horizon where it is significant for eight of the nine exchange rates and at the 36-month horizon for seven exchange rates.

significant for all but a couple of currencies at all of the medium-run horizons. For other variables, there is significance for a large number of currencies at some horizons, but not at all horizons. Again, also, we see the pattern that variables that do not perform particularly well in univariate regressions might do well in the bivariate regressions, and vice-versa.

The overall picture is that there is some evidence, using asymptotic statistics, that some economic variables are significant predictors using these within-sample tests. None perform as well as the level of the exchange rate itself, and, in any case, the evidence points toward including the level of the exchange rate with the measure of global risk in the econometric model for forecasting changes in the exchange rates at medium horizons. We also note that the two variables that appear to be the best at forecasting exchange rates overall – linearly detrended S&P 500 and linearly detrended log of overnight repo outstanding of primary dealers – are variables that in fact may not be stationary themselves. If they instead have a unit root, then the analysis here, based on the assumption of stationarity, is not valid.

Tables 6 and 7 examine the special case in which the economic variable (the X_t variable in equations (2) and (4)) is the log of the real exchange rate, q_t.[21] There are many studies that have found that the real exchange rate, as a measure of the deviation from long-run purchasing power parity, is helpful in forecasting future changes in the nominal exchange rate, many of which are based on data prior to 2000.[22] Table 6 confirms the forecasting power of the real exchange rate, using standard asymptotic statistics (corrected for problems of serial correlation.) While there is little predictive power at the 1-month horizon, the real exchange rate appears to have significant forecasting efficacy at the 12-month, 36-month, and 60-month horizons. In many cases, the adjusted R^2 values are quite high. However, we note that with very few exceptions at these horizons, the adjusted R^2 values using the nominal exchange rate as the predictor, as reported in Table 1, are higher than the values for the real exchange rate.

Table 7 provides, in the first two panels, a side-by-side comparison of these measures of goodness of fit. In the third (rightmost) panel, we present a forecasting model that uses both the nominal and real exchange rate to predict future changes in the exchange rate. It is well known

[21] We use CPI measured real exchange rates, since CPI for AUD and NZD are only available at quarterly frequency, we use the last available quarterly CPI for the construction of monthly real exchange rates.

[22] See, for example, Mark (1995), Mark and Choi (1997), Engel et al. (2008), Jordá and Taylor (2012), and Eichenbaum et al. (2020).

that these variables are highly correlated, so there will be a high level of multicollinearity in these regressions, which will tend to increase the standard errors of the slope coefficient estimates for both the nominal and real exchange rate. Nonetheless, and surprisingly, at the 12-, 36-, and 60-month horizons, the nominal exchange rate is always highly statistically significant for each of the nine currencies, as well as for the simple average and in the panel. In comparison, the real exchange rate only retains predictive power for a few currencies at each horizon, and generally for different currencies at the different horizons. This indicates that the high values we found for *t*-statistics and adjusted R^2 in Table 1 are not arising simply because the nominal exchange rate is a proxy for the real exchange rate. That is, the regressions there appear to represent some form of stationarity of the nominal exchange rate itself, though we reassess this conclusion in section 3 using simulation methods.

Out-of-sample forecasts

We next turn to evaluating out-of-sample forecasts. The procedure for producing forecasts is the same as the one described above when the level of the exchange rate is used to forecast. We estimate a model over a fixed sample size (60 months) and produce an *h*-period ahead forecast. We use the first 60 observations to produce the first set of *h*-period ahead forecasts. That is, we forecast $s_{61+h} - s_{61}$ for $h = 1, 12, 36, 60$. We then add one month of data to the sample, drop the first observation and re-estimate the model and produce forecasts of $s_{62+h} - s_{62}$ for $h = 1, 12, 36, 60$. We continue this process until the data is exhausted. We then compare forecasts of various models.

First, we directly compare the forecasts of the change in the exchange rate based on the level of the exchange rate to forecasts based on each of the measures of global risk, individually. Here we use the test proposed by Diebold and Mariano (1995) and West (1996),[23] which is appropriate because the forecasting models (models (3) and (4)) are not nested.

These comparisons for the simple average exchange rate are presented in Table 8, in the first column. A positive value for the statistic means that the forecast based on the exchange rate has a lower out of sample root mean squared error (RMSE) than the one produced by the economic variable.

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[23] Diebold and Mariano (1995) and West (1996) compare the forecasting ability of two non-nested model and conduct statistical inferences based on mean squared prediction errors.

At the one-month horizon, there is no statistically significant difference in the forecasting power of the two models. The level of the exchange rate usually produces the lower RMSE, but there are two exceptions. At the longer horizons of 12-, 36- and 60-months, the forecast based on the level of the exchange rate has a lower RMSE than any of the economic variables in all cases. In all but a few cases these differences are significant at the 36-month horizon, and they are significantly different at the one percent level in all cases at the 60-month horizon.[24]

More generally, we can ask whether we can use the level of the exchange rate alongside one of the measures of global economic risk to produce better forecasts (or use the global measure to improve the forecast from the level of the exchange rate.) Those are the questions addressed in the second and third columns of Table 8 for the average exchange rate. In the second column we ask whether the bivariate model (the one in which both the exchange rate and one economic variable are used to generate forecasts, as in equation (2)) produces significantly lower RMSE than the univariate model which includes only the economic measure of global risk (equation (4).) Here the appropriate test is the one proposed by Clark and West (2006) for nested models. We see that at the one-month horizon, while the addition of the exchange rate almost always produces better forecasts (lower RMSE), the difference is not significant. However, the picture changes dramatically at the 12-, 36- and 60-month horizons. In almost all cases, the forecasts of the bivariate model are significantly better at the ten percent than the univariate model that uses only the measure of global risk, and at the 60-month horizon the confidence level is greater than 99 percent in all cases.

The third column of Table 8 shows the Clark-West statistics for the test of whether the bivariate model (equation (2)) improves on the forecasts of the univariate model that uses the level of the exchange rate only (equation (3).) We see that in some of the cases, particularly at the 1-year horizon, the addition of the global risk variable does significantly improve the forecast.

The final column of Table 8 tests whether the univariate forecasting model based on the global risk variable (model (4)) can produce forecasts with lower mean-squared error than the random walk model (model (5).) At the longer horizons of 36- and 60- months, all these variables

[24] The exception is for the measure of commercial paper held by primary dealers. The forecasts based on the exchange rate are significantly better at only the five percent level in this case.

improve on the random walk forecast.[25] The models compared here ((4) and (5)) are restricted versions of the ones mentioned in the previous paragraph ((2) and (3)), in that they restrict the coefficient on the level of the exchange rate to be zero.

If the nominal exchange rate is stationary, researchers ought to consider testing their model including the level of the nominal exchange rate as in equation (2) against the null of equation (3) rather than the typical approach that tests equation (4) compared to the null of equation (5). We propose this alternative tack because the evidence presented so far indicates that the level of the exchange rate has forecasting power. The small-sample statistics presented in section 3 greatly moderate that conclusion, but still leave room for the possibility that the exchange rate is stationary and useful in forecasting future changes in the exchange rate.

Table 8 reports detailed forecasting results for the simple average exchange rate. Table 9 summarizes the forecasting outcomes for the nine individual exchange rates. We count the number of currencies that have a significant statistic at 5 percent significance level. The conclusions are very similar from these exchange rates as for the average exchange rate. In direct comparisons between the forecasting power of the exchange-rate level versus the global risk variable, there are essentially no significant differences at the 1- and 12-month horizons, but at the 36- and 60-month horizons the level of the exchange rate is often significantly better. It is almost always true at the 12-, 36-, and 60-month horizons that the bivariate model (such as (2)) produces significantly better forecasts than the model based only on the global risk variable (as in (4).) For some of the currencies, the bivariate model also outforecasts the model based only on the level of the exchange rate (equation (3).) But for all but a few currencies, the global risk model beats the random walk (model (4) versus (5).)

Tables 10 and 11 examine the special case in which the real exchange rate is used to forecast changes in the nominal exchange rate – that is, the case in which q_t is the measure of the economic variable X_t that appears in equations (2) and (4). Table 10 shows that the real exchange rate has significant forecasting power (using the asymptotic distribution of the Clark-West statistic, correcting for serial correlation) for changes in the nominal exchange rate at the 12-, 36- and 60-month horizons (but not at the one month), which is consistent with much of the earlier literature.

[25] The test statistics in the fourth column are slightly different across rows in the table with in each forecast horizon when the exchange rate is used as the predictor because the sample period is changed to match the period for which data is available for the global risk variable.

Table 11 then compares the forecasting power for $s_{t+h} - s_t$, $h = 1, 12, 26, 60$ of s_t and q_t. The first column of Table 11 makes the non-nested comparison of the univariate forecasting models. As indicated by the positive values for the Diebold Mariano West statistics, the nominal exchange rate almost always produces a lower out of sample mean-squared forecast error than the real exchange rate. However, it is significantly better in only a few cases at the 36- and 60-month horizons.

The second column of Table 11 looks at how the bivariate regression (including both s_t and q_t as regressors) might improve on the univariate models. While there is not much statistical significance at the 1-month horizon, at the longer horizons (12-, 36-, and 60-month), the bivariate model in general is better than either univariate model. That is, using each of the univariate models as the null model, nested in the bivariate model, we find that the more general model outperforms the null model by the Clark-West metric. At the 60-month horizon, the bivariate model rejects at the 5 percent level the univariate model that uses only q_t as the predictor for six of the nine currencies, but the bivariate model rejects the univariate model using only s_t at this level for only three currencies.

The final column compares the out-of-sample tests of each univariate model against the random walk. Here we see that for almost all cases, both univariate models significantly outforecast the random walk according to the Clark-West statistic at the longer horizons, but none do at the 1-month horizon. Again, we note that if we are interested in gauging the forecasting power of the real exchange rate and assume both the real and nominal exchange rate are stationary, we might supplement the usual test (the univariate forecast model based on q_t relative to the random walk, reported in column (5) of Table 11), with the model that sets the null as equation (3) and asks whether adding the real exchange rate as an additional predictor improves the forecasts (as reported in column (3) of Table 11).

Rolling Regressions

In Table 12, we display the sample distribution of R^2 values for the forecasting models based on the level of the exchange rate and based on the twelve global risk variables, for the simple average exchange rate.[26] Because it is common for exchange-rate papers to report sub-sample findings, we merely note here that while some of the models based on global measures of uncertainty produce very good fits over some subsamples, the forecasting model based on the level of the exchange rate generally produces even better ones. Table 13 presents a currency-by-currency table of the distribution of the R^2 values when the real exchange rate is the predictor.

The main takeaway, for now, from these tables is that while some of the values of the economic variables produce very good levels of in-sample fit over some periods, these distributions still do not look as "impressive" as the analogous table (Table 3) when the level of the nominal exchange rate is the variable used for making predictions. We shall see in the next section, however, that even Table 3 may be misleading – that such seeming strong predictive power over certain sub-samples can arise even when the exchange rate is a pure random walk.

2.e Economic Theory

It is theoretically more plausible that the nominal exchange rate incorporates a unit root, rather than being stationary. Most advanced countries are perceived as targeting inflation, usually at a level of around two percent per year, and the target is independent of inflation rates in other countries, and independent of the nominal exchange rate. Benigno and Benigno (2008) show in a standard two-country New Keynesian open-economy model in which monetary policymakers follow an instrument rule in which the interest rate in each country responds to the country's own inflation rate and output gap, and which may include an interest-rate smoothing term, the nominal exchange rate must have a unit root. Only if one of the policy rules explicitly target the nominal exchange rate will the possibility of stationary nominal exchange rates arise. Intuitively, in the floating exchange rate model, if the real exchange rate is stationary, the nominal exchange rate has a permanent component that is equal to the difference in the permanent components of prices in the two countries. If the real exchange rate is stationary, the nominal exchange rate tends to adjust to the price level differentials to bring the economy toward the long-run real exchange rate, which is reflected in the transitory component of the nominal exchange rate.

The countries in our sample avowedly do not target nominal exchange rates, so theory supplies us with a strong prior that these exchange rates have a unit root.

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[26] The conclusions from the individual exchange rates, not displayed in order to save space, deliver a very similar message as for the simple average exchange rate.

In fact, Engel and West (2005) have demonstrated that a large range of exchange rate models have the further implication that changes in the nominal exchange rate are nearly unpredictable. That is, not only does the nominal exchange rate have a unit root, but it is not distinguishable in typical sample sizes from a pure random walk.

3. Small-Sample Test Statistics using Simulation Methods

The small-sample bias for long-horizon forecasts has been extensively studied, but we find that this bias is unusually large for U.S. dollar exchange rates since 2000.[27] Very large *t*-statistics and very high R^2 values are nonetheless not statistically significant at standard significance levels, once we have accounted for small-sample biases. Tables 14, 15, and 16 present distributions of the statistics displayed in Tables 1, 2, and 3, respectively, but using simulations methods to account for small-sample biases.

As we noted at the outset, it is particularly easy to simulate the distribution of our test statistics under the null of a random walk in the exchange rate, or $s_{t+1} - s_t = \varepsilon_{t+1}$, where ε_{t+1} is an i.i.d. random variable that is not forecastable at time t.[28] Our methods of simulations are standard and described in detail in the appendix. In short, for the univariate regressions, we take the sample distribution of $s_{t+1} - s_t$ for each exchange rate. For Monte Carlo simulations, we construct artificial i.i.d. data that has the same variance as the variance of the sample data and is drawn from a Normal distribution. For bootstraps, we sample randomly from the empirical distribution, and construct artificial data. In the case of the panel regressions, for the Monte Carlo simulations, we construct vectors of Normal i.i.d. random variables that have the same covariance matrix as the data. For the bootstrap exercises, we draw randomly from the empirical distribution of the vector of exchange rate changes.

For each artificial sample, we start with s_t equal to its mean value in the data, then we discard the first 2000 values of $s_{t+1} - s_t$ to eliminate start-up bias. We then construct T values of s_t that we use in the simulations. We run 5000 simulations for each exchange rate (and for the panels) for the Monte Carlo and bootstrap exercises in order to construct the distributions of the

[27] See, for example, in the economics and finance literature, Richardson and Stock (1989), Kim et al. (1991), Hodrick (1992), Richardson (1993), Mark (1995), Berkowitz and Giorgianni (2001), Rossi (2005, 2013), Campbell and Yogo (2006), Ang and Bekaert (2007), Boudouhkh et al. (2008, 2020) and many others.

[28] Except up to a constant, which is immaterial here.

statistics we report in Tables 14-16. We note here that there is very little difference in the inferences based on the Monte Carlo compared to the bootstrap.

Within-sample Forecasts

Table 14 reports the simulated distribution for the results reported in Table 1. For each of the 1-month, 12-month, 36-month, and 60-month horizons, the table reports the slope coefficient estimate, the *t*-statistic and the R^2 from regression (1) that are reported in Table 1. It then presents the *p*-values for one-sided tests (negative slope coefficient, positive R^2), meaning the critical value at which the null hypothesis of a random walk would be rejected.[29]

In Table 1, the null hypothesis of a random walk appears to be rejected strongly at the horizons longer than one month. However, Table 14 shows that in the simulated distributions, there is not strong evidence against the random walk. At the 1-month horizon, the *p*-values reported are all quite large. The smallest is around 0.40, and most are greater than 0.50. That accords with our conclusions using asymptotic statistics, that there is little predictability at the 1-month horizon.

In contrast to our conclusions from Table 1, we find little strong evidence of predictability at the longer horizons in the simulated distributions. There are no currencies at the 12-month for which the *p*-value is less than 0.20, or at the 36-month horizons for which the smallest *p*-value is 0.12. Most are much larger than these values. The *p*-value for the adjusted R^2 for the panel regression at the 36-month horizon is 0.11, which is smaller than any of the *p*-values reported for the individual currencies, and we note that this *p*-value is considerably smaller than even the corresponding values for the slope coefficient and for the *t*-statistic for the panel regression.

At the 60-month horizon, again, in the overwhelming majority of cases there is little evidence against the random walk. The smallest *p*-value for the coefficient estimate is 0.14 for the Japanese yen. For the *t*-statistic, the *p*-value for the New Zealand dollar is 0.05 and 0.08 for the euro, but the rest are all greater than 0.15. Looking at the R^2, again for the New Zealand dollar and also for the simple average exchange rate, the *p*-value is on the smaller side, at 0.09, and the *p*-value is 0.07 for the euro. We find that the R^2 for the panel data is marginally significant at

[29] The *p*-values for two-sided tests on the slope coefficient and *t*-statistic would be approximately doubled.

standard levels using the small-sample distribution, with a *p*-value of 0.05, but the slope coefficient and *t* statistic are not significant.

On the whole, we can conclude that there is little strong evidence to reject the null of a random walk. If one were willing to consider rejection levels higher than is standard, such as 0.20, then there is more evidence that the level of the exchange rate can predict changes in the exchange rate at the 60-month horizon. That is, we hesitate to say that the in-sample evidence random walk is definitive, though our priors based on economic theory and based on the literature that has looked at pre-2000 data incline us not to reject the random walk null.

Out-of-Sample Forecasts

Table 15 reports the *p*-values for the Clark-West statistics from Table 2, using the simulated distribution. Here, again, we see that there is a noteworthy small-sample bias. In Table 2, the out-of-sample test rejected a random walk at all horizons longer than 1 month. But the *p*-values from the sample distribution do not show evidence of exchange-rate forecastability.

At all horizons, the *p*-values for the Clark-West statistic in the simulated data are large, with the exception of the euro. At horizons of 1-, 12-, and 36-months, all of these values are greater than 0.30, except for the Canadian dollar at the 12- and 36-month horizon (0.24 and 0.29, respectively) and the euro at those same horizons (0.23 and 0.05, respectively.) At the 60-month horizon, the *p*-values are still high, the lowest being for the Japanese yen (0.25), the Australian dollar (0.20), the British pound (0.25) and the euro (0.03). Only for the dollar/euro rate would we reject the null of the random walk at conventional levels.

Moreover, note that our in-sample forecast evidence rejects the random walk only for the New Zealand dollar at standard levels, while the out-of-sample case is for the euro. The random walk is not close to being rejected out-of-sample for the New Zealand dollar. We note also that while within-sample, the panel model seemed to offer relatively strong evidence against the random walk, that finding does not carry over to the out-of-sample forecasts.

We conclude that, generally we cannot reject the random walk hypothesis, though there is marginal evidence of predictability both in-sample and out-of-sample for the dollar/euro exchange rate.

Rolling R-squared

Finally, Table 16 demonstrates the fallacy in drawing conclusions from subs-samples of the data. That is, the model might fit well over sub-samples by random chance, but a great deal of care should be taken in drawing conclusions from such a finding. The table reports the 95th and 90th percentile of the R^2 values from the rolling regressions used to construct the Clark-West statistic. We showed in Table 3 that for many currencies, these sub-sample R^2 values could be very large. However, Table 16 exhibits the corresponding R^2 values when the data is generated under a random walk – and there is no systematic difference than in the actual data. That is, the high R^2 reported in some sub-samples of the true data could easily have occurred even though the true R^2 is zero. The sole exception to this, interestingly, is at the 1-month horizon, where the 95th percentile of the R^2 values from the panel model are unlikely to have been generated by an exchange rate that follows a pure random walk.

An Example of Bias in Forecast based on Measure of Risk

Here we present an example of an assessment of small-sample bias for forecasts based on one of the economic measures of global risk that we have examined, the GZ spread. We choose this measure because it is one that performs reasonably well in a univariate model of exchange rate forecasts.

As we have noted, there are many ways to approach the small-sample assessment of these forecasts. In brief, our procedure is to estimate a vector autoregression for $y_t = (s_t, x_t)'$ where x_t is the GZ spread. We can write the VAR as:

(6) $y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots \Phi_k y_{t-k} + e_t$.[30]

As Hamilton (1994, pp. 579-580) discusses, the parameters of this VAR are consistently estimated whether or not s_t and x_t have unit roots, and if they do have unit roots, whether or not they are cointegrated. We then attempt to correct for small sample bias in these VAR estimates using the bootstrap-after-bootstrap procedure of Kilian (1998).

[30] In our application, we choose a lag length of two based on the AIC. See Appendix 3 for the estimation details.

Our simulation procedure then creates artificial data for s_t by Monte Carlo methods as described above, assuming the exchange rate is generated by a driftless random walk with variance given by the sample variance of the change in the exchange rate. We create artificial data for x_t based on the estimated VAR from (6), using the estimated parameters for the x_t process and the estimated covariance matrix of e_t.

Table 17 reports the outcome of this exercise, using the GZ variable to forecast the simple average of the exchange rates. The first panel assesses the p-value for the estimated slope coefficient, t-statistic and adjusted R^2 for the in-sample forecasts based on the GZ spread. We see that none are significant at the five percent level for any of the forecast horizons.

The second panel looks at the Clark-West statistic using 5-year rolling samples to forecast at the horizons of 1, 12, 36, and 60 months. Again, we see that the p-values for the actual CW statistics from the data are all greater than 0.05, although at the 36-month horizon the p-value is 0.07.

The final panel examines the in-sample goodness of fit of the rolling regressions that were used for out-of-sample forecasting in the previous exercise. Although some of the R^2 values estimated from the data are quite high, we find that they are consistent with what we find if the exchange rate is a random walk, in that the p-values are all greater than five percent (for the 90th and 95th percentile of estimated R^2 values from the rolling regressions.)

So, using asymptotic inference, it appeared that the GZ variable had significant predictive power for changes in exchange rates at medium horizons, but that conclusion does not hold up when compared to the findings from the probability distributions from our simulations.

4. Conclusions

To reiterate, there are two main conclusions. First, based on small-sample distributions generated from simulations, there is little conclusive evidence that the level of the exchange rate helps to forecast future changes. This should give researchers some reason to pause, since the level of the exchange rate seems to have greater forecasting power than measures of global risk that are alleged to forecast the dollar in the 21st century. It is important to investigate the small-sample properties of medium- and long-run forecasting models.

Second, it is difficult to distinguish with certainty whether the nominal exchange rate or any other variable has a unit root versus the alternative that it is stationary but very persistent. However, we find that persistent global risk variables do not seem to have additional forecasting power when the level exchange rate is included as a predictor.

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Table 1: Regression statistics of in sample forecasting: $s_{t+h} - s_t = \alpha + \beta s_t + e_{t+h}$

	1-month horizon forecast (h=1)		1-year horizon forecast (h=12)		3-year horizon forecast (h=36)		5-year horizon forecast (h=60)	
	Beta	Adjusted R^2	Beta	Adjusted R^2	Beta	Adjusted R^2	Beta	Adjusted R^2
Currency	(1)	(2)	(3)	(4)	(3)	(4)	(5)	(6)
AUD	-0.016	0.004	-0.224***	0.113	-0.672***	0.453	-1.030***	0.727
	(0.011)		(0.110)		(0.142)		(0.138)	
CAD	-0.017	0.006	-0.191***	0.111	-0.622***	0.401	-1.125***	0.732
	(0.010)		(0.091)		(0.204)		(0.178)	
CHF	-0.011	0.002	-0.123***	0.084	-0.404***	0.478	-0.606***	0.710
	(0.009)		(0.074)		(0.079)		(0.099)	
EUR	-0.019	0.005	-0.257***	0.131	-0.733***	0.517	-1.122***	0.776
	(0.013)		(0.118)		(0.143)		(0.105)	
GBP	-0.013	0.000	-0.216***	0.075	-0.618***	0.217	-1.250***	0.436
	(0.011)		(0.153)		(0.298)		(0.342)	
JPY	-0.023	0.008	-0.283***	0.143	-0.946***	0.490	-1.283***	0.682
	(0.013)		(0.140)		(0.198)		(0.263)	
NOK	-0.008	-0.002	-0.193***	0.073	-0.652***	0.328	-1.262***	0.600
	(0.012)		(0.112)		(0.240)		(0.217)	
NZD	-0.020	0.007	-0.252***	0.139	-0.712***	0.570	-0.964***	0.817
	(0.012)		(0.129)		(0.121)		(0.073)	
SEK	-0.018	0.003	-0.301***	0.127	-0.764***	0.417	-1.244***	0.689
	(0.012)		(0.141)		(0.206)		(0.174)	
SA	-0.014	0.002	-0.219***	0.111	-0.689***	0.475	-1.111***	0.759
	(0.011)		(0.114)		(0.169)		(0.152)	
Panel	-0.015	0.003	-0.217***	0.107	-0.657***	0.419	-1.030***	0.661
	(0.008)		(0.091)		(0.125)		(0.097)	
Observations								
Single	254		243		219		195	
Panel	2286		2187		1971		1755	

Notes: SA is the regression with simple average of all nine currencies. * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron (1988) test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$) and Choi (2001) test statistics for panel regressions. Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags in parentheses.

Table 2: 5 year rolling window out-of-sample prediction error: $s_{t+h} - s_t = \alpha + \beta_{t-60,t} s_t$ vs random walk model ($s_{t+h} - s_t = 0$)

Clark West Statistics	1-month horizon forecast (*h*=1)	1-year horizon forecast (*h*=12)	3-year horizon forecast (*h*=36)	5-year horizon forecast (*h*=60)
Currency	(1)	(2)	(3)	(3)
AUD	-1.067	1.292*	2.927***	4.476***
CAD	-0.127	2.896***	3.861***	3.066***
CHF	-0.024	2.813***	2.257**	2.756***
EUR	0.043	3.988***	3.833***	7.981***
GBP	-1.501	2.275**	2.192**	4.101***
JPY	-0.903	1.839**	2.355***	3.918***
NOK	-1.360	2.495***	2.769***	2.087**
NZD	-0.438	1.693**	2.289**	3.830***
SEK	-0.679	2.102**	2.311**	1.988**
SA	-0.975	1.848**	3.444***	2.957***
Panel	-0.493	2.001**	4.300***	5.018***

Notes: SA is the regression with simple average of all nine currencies. * p<0.1, ** p<0.05, *** p<0.01 for one-sided test. Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with *h*-1 lags in parentheses.

Table3

Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_{t+h}$

Currency	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
				1-month horizon forecast				
AUD	-0.02	0.00	0.02	0.04	0.08	0.10	0.16	0.20
CAD	-0.02	-0.01	0.02	0.04	0.07	0.15	0.22	0.26
CHF	-0.02	0.02	0.04	0.07	0.13	0.21	0.24	0.25
EUR	-0.02	0.00	0.02	0.08	0.10	0.13	0.15	0.17
GBP	-0.02	-0.01	0.01	0.05	0.10	0.14	0.21	0.27
JPY	-0.02	-0.01	0.02	0.04	0.06	0.08	0.14	0.15
NOK	-0.02	-0.01	0.02	0.05	0.13	0.15	0.20	0.21
NZD	-0.02	0.02	0.03	0.06	0.10	0.12	0.17	0.24
SEK	-0.02	-0.01	0.02	0.04	0.08	0.09	0.13	0.20
SA	-0.02	0.00	0.02	0.03	0.09	0.13	0.20	0.20
Panel	-0.02	0.00	0.02	0.04	0.06	0.09	0.12	0.14
				1-year horizon forecast				
AUD	-0.02	0.18	0.38	0.51	0.64	0.70	0.75	0.75
CAD	-0.02	0.04	0.39	0.59	0.66	0.72	0.83	0.84
CHF	-0.02	0.21	0.34	0.53	0.70	0.78	0.84	0.85
EUR	-0.01	0.20	0.41	0.66	0.71	0.74	0.84	0.85
GBP	-0.02	0.18	0.33	0.50	0.76	0.79	0.90	0.90
JPY	-0.02	0.05	0.38	0.51	0.68	0.72	0.77	0.77
NOK	-0.02	0.06	0.45	0.69	0.75	0.79	0.83	0.83
NZD	-0.02	0.33	0.52	0.64	0.71	0.72	0.76	0.77
SEK	0.02	0.22	0.52	0.62	0.64	0.66	0.70	0.71
SA	-0.02	0.17	0.50	0.57	0.64	0.70	0.82	0.83
Panel	0.03	0.24	0.40	0.49	0.57	0.62	0.71	0.72

Notes: SA is the regression with simple average of all nine currencies. Adjusted R^2 are reported. Panel regressions include country fixed effect.

Table3 (continued)

Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_{t+h}$

Currency	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
3-year horizon forecast								
AUD	-0.02	0.24	0.58	0.76	0.83	0.85	0.89	0.89
CAD	0.00	0.25	0.51	0.63	0.77	0.83	0.94	0.94
CHF	-0.02	0.05	0.62	0.76	0.83	0.85	0.87	0.88
EUR	-0.01	0.22	0.57	0.65	0.71	0.81	0.91	0.91
GBP	0.07	0.29	0.44	0.67	0.91	0.93	0.93	0.93
JPY	0.07	0.43	0.70	0.86	0.91	0.95	0.96	0.96
NOK	0.00	0.28	0.42	0.55	0.71	0.81	0.92	0.92
NZD	0.03	0.39	0.63	0.77	0.81	0.84	0.88	0.89
SEK	0.16	0.32	0.46	0.65	0.71	0.73	0.81	0.81
SA	0.06	0.20	0.54	0.68	0.75	0.80	0.91	0.91
Panel	0.35	0.48	0.62	0.71	0.78	0.81	0.86	0.87
5-year horizon forecast								
AUD	0.02	0.46	0.63	0.72	0.83	0.91	0.92	0.93
CAD	0.31	0.51	0.58	0.66	0.75	0.82	0.87	0.88
CHF	0.00	0.29	0.69	0.94	0.95	0.95	0.96	0.96
EUR	0.09	0.27	0.65	0.78	0.80	0.81	0.84	0.84
GBP	0.11	0.51	0.79	0.89	0.93	0.94	0.94	0.94
JPY	-0.02	0.08	0.79	0.91	0.96	0.96	0.97	0.97
NOK	0.20	0.33	0.47	0.60	0.67	0.73	0.76	0.77
NZD	0.01	0.67	0.77	0.80	0.85	0.89	0.90	0.90
SEK	0.27	0.44	0.59	0.72	0.76	0.78	0.81	0.81
SA	0.24	0.56	0.63	0.71	0.75	0.83	0.86	0.87
Panel	0.58	0.67	0.70	0.77	0.82	0.84	0.85	0.85

Notes: SA is the regression with simple average of all nine currencies. Adjusted R^2 are reported. Panel regressions include country fixed effect.

Table 4
Regression statistics of in sample forecasting using simple average of exchange rate:
$s_{t+h} - s_t = \alpha + \beta^X X_t + e_{t+h}$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_{t+h}$ and $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{ss} s_t + e_{t+h}$

		Univariate model		Univariate model		Bivariate model		
		β^X	Adjusted R^2	β^s	Adjusted R^2	β^{XX}	β^{ss}	Adjusted R^2
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1-month horizon forecast (h=1)	US Treasury premium	-0.539	0.008	-0.015	0.004	-0.763	-0.024	0.021
	MAR global factor	-0.001	0.000	-0.014	0.003	-0.000	-0.012	0.001
	GZ spread	0.000	-0.003	-0.014	0.002	0.000	-0.013	-0.001
	Log SP500	-0.008**	0.025	-0.014	0.002	-0.013***	-0.036**	0.057
	Log VIX	0.001	-0.002	-0.014	0.002	0.001	-0.013	-0.001
	US Term spread (5y-FF)	0.001	0.003	-0.014	0.002	0.001	-0.015	0.006
	US Term spread (10y-2y)	0.001	0.004	-0.014	0.002	0.002**	-0.022	0.015
	TED	-0.003	0.009	-0.014	0.002	-0.003	-0.013	0.011
	Intermediary leverage	-0.008	-0.004	-0.015	0.004	-0.081*	-0.038	0.015
	Interm. weighted return	-0.004	-0.004	-0.015	0.004	-0.003	-0.015	-0.000
	Log Repo	0.002	0.001	-0.014	0.003	0.006**	-0.038*	0.026
	Log Commercial Paper	-0.007	0.006	-0.021	0.009	-0.006	-0.017	0.010
1-year horizon forecast (h=12)	US Treasury premium	-0.388	-0.004	-0.227***	0.121	-2.823	-0.258***	0.137
	MAR global factor	-0.010	0.060	-0.219***	0.111	-0.006	-0.183***	0.127
	GZ spread	0.011**	0.086	-0.219***	0.111	0.010**	-0.193***	0.170
	Log SP500	-0.076***	0.166	-0.219***	0.111	-0.138***	-0.446***	0.536
	Log VIX	0.025	0.045	-0.219***	0.111	0.017	-0.196***	0.130
	US Term spread (5y-FF)	0.010	0.049	-0.219***	0.111	0.011	-0.226***	0.169
	US Term spread (10y-2y)	0.007	0.024	-0.219***	0.111	0.014	-0.292***	0.202
	TED	-0.015	0.018	-0.219***	0.111	-0.014	-0.218***	0.129
	Intermediary leverage	-0.020	-0.004	-0.222***	0.114	-0.98***	-0.505***	0.270
	Interm. weighted return	-0.027	-0.002	-0.222***	0.114	-0.023	-0.221***	0.112
	Log Repo	0.015	0.017	-0.237***	0.130	0.069***	-0.533***	0.396
	Log Commercial Paper	-0.067	0.055	-0.355***	0.271	-0.025	-0.337***	0.276

Notes: Inferences are based on Newey West standard errors with h-1 lags. * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$) for s_t and two-sidedd test based on t-distribution for macro variables. Regressions with s_t matches the sample period of each global variable. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Refer to the Data Appendix for the number of observations.

Table 4 (continued)

Regression statistics of in sample forecasting using simple average of exchange rate:

$s_{t+h} - s_t = \alpha + \beta^X X_t + e_{t+h}$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_{t+h}$ and $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{ss} s_t + e_{t+h}$

		Univariate model		Univariate model		Bivariate model		
		β^X	Adjusted R^2	β^s	Adjusted R^2	β^{XX}	β^{ss}	Adjusted R^2
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-year horizon forecast (h=36)	US Treasury premium	5.480	0.030	-0.689***	0.475	-1.167	-0.701***	0.474
	MAR global factor	-0.011	0.023	-0.689***	0.475	0.006	-0.720***	0.479
	GZ spread	0.027**	0.194	-0.689***	0.475	0.020***	-0.626***	0.573
	Log SP500	-0.001	-0.005	-0.689***	0.475	-0.130***	-0.892***	0.615
	Log VIX	0.069**	0.136	-0.689***	0.475	0.038	-0.634***	0.512
	US Term spread (5y-FF)	0.008	0.009	-0.689***	0.475	0.009	-0.693***	0.492
	US Term spread (10y-2y)	-0.005	0.000	-0.689***	0.475	0.013	-0.750***	0.502
	TED	0.018	0.010	-0.689***	0.475	0.018	-0.688***	0.487
	Intermediary leverage	0.937	0.130	-0.689***	0.475	-0.844	-0.933***	0.521
	Interm. weighted return	-0.099**	0.006	-0.689***	0.475	-0.087**	-0.687***	0.481
	Log Repo	-0.021	0.014	-0.741***	0.553	0.098***	-1.151***	0.775
	Log Commercial Paper	0.008	-0.005	-0.819***	0.590	0.121***	-0.911***	0.661
5-year horizon forecast (h=60)	UST premium	10.590*	0.073	-1.111***	0.759	0.255	-1.108***	0.757
	MAR global factor	-0.011	0.011	-1.111***	0.759	0.016*	-1.186***	0.787
	GZ spread	0.022	0.071	-1.111***	0.759	0.007	-1.086***	0.766
	Log SP500	0.129**	0.105	-1.111***	0.759	-0.038	-1.169***	0.765
	Log VIX	0.067	0.070	-1.111***	0.759	0.001	-1.110***	0.757
	US Term spread (5y-FF)	-0.014	0.020	-1.111***	0.759	-0.010	-1.104***	0.772
	US Term spread (10y-2y)	-0.038**	0.179	-1.111***	0.759	-0.014	-1.045***	0.780
	TED	0.037	0.031	-1.111***	0.759	0.035***	-1.109***	0.791
	Intermediary leverage	2.157***	0.431	-1.111***	0.759	-0.135	-1.152***	0.758
	Interm. weighted return	-0.010	-0.005	-1.111***	0.759	0.010	-1.111***	0.758
	Log Repo	-0.065	0.089	-1.129***	0.763	0.099***	-1.525***	0.888
	Log Commercial Paper	0.014	-0.005	-1.190***	0.751	0.167***	-1.305***	0.830

Notes: Inferences are based on Newey West standard errors with h-1 lags. * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$) for s_t and two-sided test based on t-distribution for macro variables. Regressions with s_t matches the sample period of each global variable. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Refer to the Data Appendix for the number of observations. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 5

Summary of regression statistics of in sample forecasting for each currency: For each horizon, we run regressions of $s_{t+h} - s_t = \alpha + \beta^X X_t + e_{t+h}$ and $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{SS} s_t + e_{t+h}$ for each currency. we Log Report the count of significant coefficients of the first regression in the first column, and the count of significant coefficients of the second regression in the second column in the format of $\beta^{XX} - \beta^{SS}$.

		Univariate model	Bivariate model		Univariate model	Bivariate model
		β^X	$\beta^{XX} - \beta^{ss}$		β^X	$\beta^{XX} - \beta^{ss}$
Independent variables		(1)	(2)		(1)	(2)
US Treasury premium		2	3 - 1		4	1 – 9
MAR global factor		1	0 - 0		2	0 – 9
GZ spread		0	0 - 0		8	7 – 8
Log SP500		5	8 - 4		1	7 - 7
Log VIX		0	0 - 0		7	1 – 9
US Term spread (5y-FF)	1-month horizon forecast (h=1)	1	1 - 0	3-year horizon forecast (h=36)	0	1 – 9
US Term spread (10y-2y)		2	5 - 0		2	1 – 9
TED		2	2 - 0		2	2 – 9
Intermediary leverage		0	5 - 0		3	5 – 9
Interm. weighted return		0	0 - 0		6	6 – 9
Log Repo		0	6 - 3		0	8 – 9
Log Commercial Paper		2	1 - 0		3	8 - 9
US Treasury premium		1	1 – 9		5	0 - 9
MAR global factor		1	0 - 9		3	5 - 9
GZ spread		7	5 – 9		3	2 - 9
Log SP500		8	9 - 8		6	3 - 9
Log VIX		3	1 – 9		4	2 - 9
US Term spread (5y-FF)	1-year horizon forecast (h=12)	2	2 – 9	5-year horizon forecast (h=60)	2	1 - 9
US Term spread (10y-2y)		1	4 – 9		7	2 - 9
TED		1	1 – 9		3	7 - 9
Intermediary leverage		0	7 – 9		9	5 - 9
Interm. weighted return		0	0 – 9		0	0 - 9
Log Repo		0	7 – 9		2	8 - 9
Log Commercial Paper		4	2 - 9		2	7 - 9

Notes: Nine sample countries in total. We count the coefficient that is above 5% significance level (one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$) for s_t and two-sidedd test based on t-distribution for macro variables). Significance are based on Newey West standard errors with h-1 lags. Regressions with s_t matches the sample period of each global variable. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 6
Regression statistics of in sample forecasting using real exchange rate: $s_{t+h} - s_t = \alpha + \beta q_t + e_{t+h}$

	1-month horizon forecast (h=1)		1-year horizon forecast (h=12)		3-year horizon forecast (h=36)		5-year horizon forecast (h=60)	
	Beta	Adjusted R^2	Beta	Adjusted R^2	Beta	Adjusted R^2	Beta	Adjusted R^2
Currency	(1)	(2)	(3)	(4)	(3)	(4)	(5)	(6)
AUD	-0.011	0.002	-0.157***	0.080	-0.553***	0.440	-0.886***	0.765
	(0.009)		(0.100)		(0.145)		(0.124)	
CAD	-0.015	0.001	-0.183***	0.064	-0.708***	0.314	-1.422***	0.662
	(0.012)		(0.106)		(0.237)		(0.239)	
CHF	-0.021	0.003	-0.181***	0.047	-0.468***	0.118	-1.099***	0.318
	(0.016)		(0.122)		(0.382)		(0.184)	
EUR	-0.016	0.002	-0.256***	0.106	-0.766***	0.429	-1.266***	0.654
	(0.013)		(0.108)		(0.208)		(0.117)	
GBP	-0.014	-0.001	-0.301***	0.094	-0.738***	0.191	-1.364***	0.294
	(0.014)		(0.154)		(0.370)		(0.357)	
JPY	-0.002	-0.004	-0.038***	0.006	-0.150***	0.032	-0.036***	-0.004
	(0.006)		(0.057)		(0.090)		(0.174)	
NOK	-0.007	-0.003	-0.230***	0.055	-0.704***	0.202	-1.615***	0.471
	(0.016)		(0.145)		(0.337)		(0.262)	
NZD	-0.015	0.003	-0.208***	0.106	-0.656***	0.549	-0.913***	0.829
	(0.011)		(0.116)		(0.117)		(0.052)	
SEK	-0.004	-0.004	-0.115***	0.019	-0.267***	0.040	-0.827***	0.140
	(0.010)		(0.115)		(0.332)		(0.391)	
SA	-0.007	-0.003	-0.224***	0.067	-0.809***	0.319	-1.616***	0.631
	(0.012)		(0.123)		(0.324)		(0.206)	
Panel	-0.009	0.003	-0.151***	0.052	-0.497***	0.230	-0.849***	0.383
	(0.006)		(0.064)		(0.128)		(0.095)	
Observations								
Single	254		243		219		195	
Panel	2286		2187		1971		1755	

Notes: SA is the regression with simple average of all nine currencies. * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$). Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags in parentheses.

Table 7

Regression statistics of in sample forecasting using real exchange rate:

$s_{t+h}-s_t=\alpha+\beta^q q_t+e_{t+h}$, $s_{t+h}-s_t=\alpha+\beta^s s_t+e_{t+h}$ and $s_{t+h}-s_t=\alpha+\beta^{qq} q_t+\beta^{ss} s_t+e_{t+h}$

		Univariate model		Univariate model		Bivariate model		
		β^q	Adjusted R^2	β^s	Adjusted R^2	β^{qq}	β^{ss}	Adjusted R^2
	Currencies	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1-month horizon forecast (h=1)	AUD	-0.011	0.002	-0.016	0.004	0.018	-0.037	0.001
	CAD	-0.015	0.001	-0.017	0.006	0.072	-0.073**	0.010
	CHF	-0.021	0.003	-0.011	0.002	-0.021	-0.011	0.005
	EUR	-0.016	0.002	-0.019	0.005	0.013	-0.030	0.002
	GBP	-0.014	-0.001	-0.013	0.000	0.006	-0.017	-0.004
	JPY	-0.002	-0.004	-0.023	0.008	-0.001	-0.023*	0.004
	NOK	-0.007	-0.003	-0.008	-0.002	0.042	-0.038	-0.004
	NZD	-0.015	0.003	-0.020	0.007	0.174**	-0.204**	0.021
	SEK	-0.004	-0.004	-0.018	0.003	0.014	-0.029*	0.002
	SA	-0.007	-0.003	-0.014	0.002	0.019	-0.026	0.001
	Panel	-0.009	0.003	-0.015	0.003	0.001	-0.016*	0.006
1-year horizon forecast (h=12)	AUD	-0.157***	0.080	-0.224***	0.113	0.273	-0.540***	0.128
	CAD	-0.183***	0.064	-0.191***	0.111	0.716**	-0.745***	0.177
	CHF	-0.181***	0.047	-0.123***	0.084	-0.164	-0.117***	0.122
	EUR	-0.256***	0.106	-0.257***	0.131	0.063	-0.310***	0.129
	GBP	-0.301***	0.094	-0.216***	0.075	-0.352	0.044***	0.091
	JPY	-0.038***	0.006	-0.283***	0.143	-0.029	-0.280**	0.146
	NOK	-0.230***	0.055	-0.193***	0.073	0.266	-0.381***	0.075
	NZD	-0.208***	0.106	-0.252***	0.139	1.361**	-1.685***	0.226
	SEK	-0.115***	0.019	-0.301***	0.127	0.119	-0.387***	0.137
	SA	-0.224***	0.067	-0.219***	0.111	0.053	-0.252***	0.109
	Panel	-0.151***	0.052	-0.217***	0.107	-0.013	-0.209**	0.106

Notes: * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha=0$). Significance inference for s_t is based on Phillips Perron test statistics and compare to the Dickey Fuller distribution. Significance inference for q_t is based on Phillips Perron test statistics and compared to the Dickey Fuller distribution in the univariate regression (column 3-4). Significance inference for q_t is based on usual t statistics in the bivariate regression (column 5-7).

Table 7 (continued)
Regression statistics of in sample forecasting using real exchange rate:
$s_{t+h} - s_t = \alpha + \beta^q q_t + e_{t+h}$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_{t+h}$ and $s_{t+h} - s_t = \alpha + \beta^{qq} q_t + \beta^{ss} s_t + e_{t+h}$

		Univariate model		Univariate model		Bivariate model		
		β^q	Adjusted R^2	β^s	Adjusted R^2	β^{qq}	β^{ss}	Adjusted R^2
	Currencies	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-year horizon forecast (h=36)	AUD	-0.553***	0.44	-0.672***	0.453	-0.158	-0.489***	0.452
	CAD	-0.708***	0.314	-0.622**	0.401	1.388*	-1.675***	0.46
	CHF	-0.468***	0.118	-0.404***	0.478	-0.223	-0.376***	0.501
	EUR	-0.766***	0.429	-0.733***	0.517	0.411	-1.074***	0.525
	GBP	-0.738***	0.191	-0.618***	0.217	-0.167	-0.501***	0.215
	JPY	-0.15***	0.032	-0.946***	0.49	-0.144	-0.943***	0.522
	NOK	-0.704***	0.202	-0.652***	0.328	1.597**	-1.764***	0.423
	NZD	-0.656***	0.549	-0.712***	0.57	0.312	-1.041***	0.57
	SEK	-0.267***	0.04	-0.764***	0.417	0.462	-1.047***	0.492
	SA	-0.809***	0.319	-0.689***	0.475	0.240	-0.836***	0.479
	Panel	-0.497***	0.23	-0.657***	0.419	-0.043	-0.626***	0.42
5-year horizon forecast (h=60)	AUD	-0.886***	0.765	-1.030***	0.727	-1.123	0.287***	0.766
	CAD	-1.422***	0.662	-1.125***	0.732	1.351*	-2.124***	0.751
	CHF	-1.099***	0.318	-0.606***	0.710	-0.269	-0.550***	0.722
	EUR	-1.266***	0.654	-1.122***	0.776	1.658***	-2.438***	0.829
	GBP	-1.364***	0.294	-1.250***	0.436	0.206	-1.383*	0.435
	JPY	-0.036***	-0.004	-1.283***	0.682	-0.158	-1.315***	0.703
	NOK	-1.615***	0.471	-1.262***	0.600	1.117	-1.995**	0.621
	NZD	-0.913***	0.829	-0.964***	0.817	-0.817**	-0.102***	0.828
	SEK	-0.827**	0.140	-1.244***	0.689	0.750**	-1.596***	0.752
	SA	-1.616***	0.631	-1.111***	0.759	0.168	-1.209***	0.758
	Panel	-0.849***	0.383	-1.030***	0.661	-0.056	-0.991***	0.661

Notes: * p<0.1, ** p<0.05, *** p<0.01 for one-sided test based on Phillips Perron test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$). Significance inference for s_t is based on Phillips Perron test statistics and compare to the Dickey Fuller distribution. Significance inference for q_t is based on Phillips Perron test statistics and compared to the Dickey Fuller distribution in the univariate regression (column 3-4). Significance inference for q_t is based on usual t statistics in the bivariate regression (column 5-7).

Table 8: 5-year rolling window out-of-sample using simple average of exchange rate, comparing predictive accuracy of models between:

i) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1}X_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1}s_t$ (Univariate s_t vs univariate X_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1}X_t + \hat{\beta}^{ss}_{t-61,t-1}s_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1}X_t$ (Bivariate v.s. univariate X_t) (Clark West test)

iii) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1}X_t + \hat{\beta}^{ss}_{t-61,t-1}s_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1}s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1}s_t$ and $\widehat{s_{t+h}-s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1}X_t$ and $\widehat{s_{t+h}-s_t} = 0$ (Univariate X_t v.s. random walk model (r.w.)) (Clark West test)

	Independent variables	Univariate s_t vs univariate X_t	Bivariate v.s. univariate X_t	Bivariate v.s. univariate s_t	Univariate s_t v.s. r.w.	Univariate X_t v.s. r.w.
		(i)	(ii)	(iii)	(iv)	(v)
1-month horizon forecast (*h*=1)	US Treasury premium	0.88	1.72**	0.22	-0.91	-0.63
	MAR global factor	0.34	0.23	0.27	-0.88	-0.72
	GZ spread	0.47	-0.28	0.18	-0.98	0.51
	Log SP500	0.22	-0.22	1.06	-0.98	1.02
	Log VIX	0.22	0.03	-0.59	-0.98	0.16
	US Term spread (5y-FF)	0.38	0.80	-0.17	-0.98	-1.61
	US Term spread (10y-2y)	-0.03	0.52	0.15	-0.98	-1.12
	TED	0.56	-0.15	-0.39	-0.98	-0.58
	Intermediary leverage	0.43	-0.15	-0.28	-0.86	0.10
	Interm. weighted return	-0.04	0.41	-0.13	-0.86	-0.03
	Log Repo	0.84	0.24	-0.33	-0.69	0.12
	Log Commercial Paper	0.56	-0.23	0.11	-0.81	0.90
1-year horizon forecast (*h*=12)	US Treasury premium	0.30	1.62*	1.47*	1.83**	1.90**
	MAR global factor	0.28	1.54*	1.63*	1.85**	1.76**
	GZ spread	0.86	1.64*	1.13	1.85**	1.52*
	Log SP500	0.27	1.15	1.16	1.85**	3.60***
	Log VIX	0.71	1.86**	1.43	1.85**	1.25
	US Term spread (5y-FF)	1.09	2.24**	1.82**	1.85**	0.91
	US Term spread (10y-2y)	1.20	2.06**	2.01**	1.85**	0.08
	TED	0.74	1.74**	2.53***	1.85**	2.02**
	Intermediary leverage	0.89	2.15**	1.62*	1.83**	1.80**
	Interm. weighted return	0.86	1.93**	-2.05	1.83**	1.14
	Log Repo	0.64	2.24**	1.97**	1.84**	2.20**
	Log Commercial Paper	0.44	2.32**	1.54*	1.88**	2.61***

Notes: * p<0.1, ** p<0.05, *** p<0.01 for two-sided test for column (1) and one-sided test for the rest. In column (1), a positive value indicates the mean square error of univariate s_t is smaller than that of X_t.Newey-West standard errors with h-1 lags are applied. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. Regressions with s_t matches the sample period of each global variable. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 8 (continued): 5-year rolling window out-of-sample using simple average of exchange rate, comparing predictive accuracy of models between:

i) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate X_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ (Bivariate v.s. univariate X_t) (Clark West test)

iii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate X_t v.s. random walk model (r.w.)) (Clark West test)

	Independent variables	Univariate s_t vs univariate X_t	Bivariate v.s. univariate X_t	Bivariate v.s. univariate s_t	Univariate s_t v.s. r.w.	Univariate X_t v.s. r.w.
		(i)	(ii)	(iii)	(iv)	(v)
3-year horizon forecast (*h*=36)	US Treasury premium	2.38**	2.49***	0.10	3.46***	3.61***
	MAR global factor	0.86	1.77**	0.56	3.44***	2.92***
	GZ spread	0.76	2.11**	1.63*	3.44***	3.41***
	Log SP500	1.54	2.55***	0.75	3.44***	5.55***
	Log VIX	0.63	2.92***	1.98**	3.44***	2.82***
	US Term spread (5y-FF)	3.02***	3.99***	2.15**	3.44***	4.20***
	US Term spread (10y-2y)	3.38***	4.28***	0.79	3.44***	3.45***
	TED	4.72***	4.07***	1.46	3.44***	3.17***
	Intermediary leverage	2.21**	6.02***	1.10	3.64***	3.03***
	Interm. weighted return	3.51***	5.54***	1.51*	3.64***	3.13***
	Log Repo	3.78***	5.30***	1.39*	3.68***	3.11***
	Log Commercial Paper	4.21***	4.52***	0.78	3.32***	2.88***
5-year horizon forecast (*h*=60)	US Treasury premium	3.65***	3.99***	-0.02	2.96***	3.61***
	MAR global factor	3.11***	2.82***	1.55	2.96***	1.78**
	GZ spread	2.65***	3.15***	0.95	2.96***	2.01**
	Log SP500	2.63***	4.27***	-1.78	2.96***	3.67***
	Log VIX	2.80***	3.41***	0.73	2.96***	1.90**
	US Term spread (5y-FF)	4.10***	5.27***	2.30**	2.96***	3.53***
	US Term spread (10y-2y)	3.65***	4.13***	1.46*	2.96***	3.84***
	TED	3.59***	4.47***	2.82***	2.96***	2.97***
	Intermediary leverage	4.07***	5.31***	2.80***	2.96***	2.91***
	Interm. weighted return	3.57***	4.99***	-1.44	2.96***	2.91***
	Log Repo	3.52***	5.94***	1.91**	3.11***	3.46***
	Log Commercial Paper	3.39***	3.93***	2.57***	3.30***	2.71***

Notes: * p<0.1, ** p<0.05, *** p<0.01 for two-sided test for column (1) and one-sided test for the rest. In column (1), a positive value indicates the mean square error of univariate s_t is smaller than that of X_t. Newey-West standard errors with h-1 lags are applied. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. Regressions with s_t matches the sample period of each global variable. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 9

Summary of individual country 5-year rolling window out-of-sample prediction error, comparing predictive accuracy between:

i) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate X_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ (Bivariate v.s. univariate X_t) (Clark West test)

iii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate X_t v.s. random walk model (r.w.)) (Clark West test)

	Independent variables	Univariate s_t vs univariate X_t	Bivariate v.s. univariate X_t	Bivariate v.s. univariate s_t	Univariate s_t v.s. r.w.	Univariate X_t v.s. r.w.
		(i)	(ii)	(iii)	(iv)	(v)
1-month horizon forecast (h=1)	US Treasury premium	0	1	1	0	0
	MAR global factor	0	1	0	0	0
	GZ spread	0	0	0	0	0
	Log SP500	0	0	1	0	1
	Log VIX	0	0	1	0	0
	US Term spread (5y-FF)	0	0	0	0	0
	US Term spread (10y-2y)	0	3	0	0	0
	TED	0	1	0	0	0
	Intermediary leverage	0	0	0	0	0
	Interm. weighted return	0	0	0	0	0
	Log Repo	0	2	0	0	0
	Log Commercial Paper	0	0	0	0	0
1-year horizon forecast (h=12)	US Treasury premium	0	8	5	8	4
	MAR global factor	0	7	5	8	4
	GZ spread	0	6	1	7	4
	Log SP500	0	7	3	8	6
	Log VIX	0	8	2	8	3
	US Term spread (5y-FF)	0	9	4	8	2
	US Term spread (10y-2y)	1	8	3	8	0
	TED	0	6	7	8	4
	Intermediary leverage	0	9	3	8	4
	Interm. weighted return	0	9	0	8	0
	Log Repo	1	9	5	8	6
	Log Commercial Paper	0	9	4	7	6

Notes: Nine sample countries in total. We count the coefficient that is below 5% significance level. Significance are based on Newey West standard errors with h-1 lags. Regressions with s_t matches the sample period of each global variable. Regressions with s_t matches the sample period of each global variable. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 9 (continued)

Summary of individual country 5-year rolling window out-of-sample prediction error, comparing predictive accuracy between:

i) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate X_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ (Bivariate v.s. univariate X_t) (Clark West test)

iii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate X_t v.s. random walk model (r.w.)) (Clark West test)

	Independent variables	Univariate s_t vs univariate X_t	Bivariate v.s. univariate X_t	Bivariate v.s. univariate s_t	Univariate s_t v.s. r.w.	Univariate X_t v.s. r.w.
		(i)	(ii)	(iii)	(iv)	(v)
3-year horizon forecast (*h*=36)	US Treasury premium	3	9	2	9	7
	MAR global factor	1	6	1	9	6
	GZ spread	2	9	3	8	8
	Log SP500	2	9	3	9	6
	Log VIX	0	9	7	9	8
	US Term spread (5y-FF)	3	9	6	9	8
	US Term spread (10y-2y)	4	9	5	9	8
	TED	4	9	2	9	7
	Intermediary leverage	3	9	4	9	8
	Interm. weighted return	5	9	1	9	6
	Log Repo	7	9	2	9	5
	Log Commercial Paper	5	9	3	9	5
5-year horizon forecast (*h*=60)	US Treasury premium	3	9	6	9	8
	MAR global factor	7	8	3	9	6
	GZ spread	8	9	6	9	7
	Log SP500	4	9	5	9	8
	Log VIX	6	9	4	9	7
	US Term spread (5y-FF)	5	9	6	9	9
	US Term spread (10y-2y)	4	9	4	9	8
	TED	6	9	7	9	8
	Intermediary leverage	6	9	7	9	7
	Interm. weighted return	7	9	0	9	7
	Log Repo	7	9	3	9	9
	Log Commercial Paper	7	8	2	9	8

Notes: Nine sample countries in total. We count the coefficient that is below 5% significance level. Significance are based on Newey West standard errors with h-1 lags. Regressions with s_t matches the sample period of each global variable. Regressions with s_t matches the sample period of each global variable. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 10
5 year rolling window out of sample prediction error:
$s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} q_t$ vs random walk model ($s_{t+h} - s_t = 0$)

Clark West Statistics	1-month horizon forecast (*h*=1)	1-year horizon forecast (*h*=12)	3-year horizon forecast (*h*=36)	5-year horizon forecast (*h*=60)
Currency	(1)	(2)	(3)	(4)
AUD	-2.400	1.099	3.122***	3.822***
CAD	0.291	2.644***	4.373***	3.986***
CHF	0.475	2.366***	1.839**	2.015**
EUR	-0.421	3.026***	3.378***	7.672***
GBP	-1.135	3.381***	1.859**	4.453***
JPY	-0.997	0.935	1.636*	3.230***
NOK	-1.252	2.529***	2.455***	2.474***
NZD	-1.307	1.432*	2.270**	3.832***
SEK	-0.774	2.406***	2.907***	3.072***
SA	-1.386	2.008**	6.003***	5.265***
Panel	-0.712	2.150**	4.823***	10.702***

Notes: SA is the regression with simple average of all nine currencies. * $p<0.1$, ** $p<0.05$, *** $p<0.01$ for one-sided test. Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with *h*-1 lags in parentheses.

Table 11

5-year rolling window out of sample prediction error using simple real exchange rate, comparing models between:

i) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t-1} q_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate q_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{qq}_{t-61,t-1} q_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t-1} q_t$ (Bivariate v.s. univariate q_t) (Clark West test)

iii) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{qq}_{t-61,t-1} q_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t} s_t$ and $\widehat{s_{t+h}-s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t} q_t$ and $\widehat{s_{t+h}-s_t} = 0$ (Univariate q_t v.s. random walk model (r.w.)) (Clark West test)

Test statistics	Currency	(i) Univariate s_t vs univariate q_t	(ii) Bivariate v.s. univariate q_t	(iii) Bivariate v.s. univariate s_t	(iv) Univariate s_t v.s. r.w.	(v) Univariate q_t v.s. r.w.
1-month horizon forecast (h=1)	AUD	0.858	2.026**	1.888**	-1.067	-2.400
	CAD	-0.707	-0.977	-1.336	-0.127	0.291
	CHF	-0.113	2.388***	1.932**	-0.024	0.475
	EUR	1.112	1.099	0.275	0.043	-0.421
	GBP	0.098	1.579*	0.845	-1.501	-1.135
	JPY	1.020	0.853	0.532	-0.903	-0.997
	NOK	-0.225	-0.854	-0.914	-1.360	-1.252
	NZD	1.205	1.395*	0.761	-0.438	-1.307
	SEK	0.105	1.894*	1.822**	-0.679	-0.774
	SA	0.311	1.255	0.517	-0.975	-1.386
	Panel	0.891	3.371***	2.528***	-0.493	-0.712
1-year horizon forecast (h=12)	AUD	0.652	2.083**	2.287***	1.292*	1.099
	CAD	-0.674	1.381*	1.520*	2.896***	2.644***
	CHF	0.204	2.530***	3.301***	2.813***	2.366***
	EUR	0.055	1.615*	1.671**	3.988***	3.026***
	GBP	0.281	1.355*	0.107	2.275**	3.381***
	JPY	0.559	2.338***	2.345***	1.839**	0.935
	NOK	-0.300	2.606***	1.887**	2.495***	2.529***
	NZD	1.630	2.331***	2.045**	1.693**	1.432*
	SEK	0.307	2.025**	1.900**	2.102**	2.406***
	SA	-0.088	2.243**	1.783**	1.848**	2.008**
	Panel	1.348	2.906***	2.244**	2.001**	2.150**

Notes: * p<0.1, ** p<0.05, *** p<0.01 for two-sided test for the first column and one-sided test for the rest. Newey-West standard errors with h-1 lags are applied. In column (1), a positive value indicates the mean square error of univariate $s_t$is smaller than that of q_t. Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags in parentheses.

Table 11 (continued)

5-year rolling window out of sample prediction error using simple real exchange rate, comparing models between:

i) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t-1} q_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate q_t) (Diebold Mariano West test)

ii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{qq}_{t-61,t-1} q_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t-1} q_t$ (Bivariate v.s. univariate q_t) (Clark West test)

iii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{qq}_{t-61,t-1} q_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{q}_{t-61,t} q_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate q_t v.s. random walk model (r.w.)) (Clark West test)

Test statistics	Currency	(i) Univariate s_t vs univariate q_t	(ii) Bivariate v.s. univariate q_t	(iii) Bivariate v.s. univariate s_t	(iv) Univariate s_t v.s. r.w.	(v) Univariate X_t v.s. r.w.
3-year horizon forecast (*h*=36)	AUD	-1.378	1.483*	2.863***	2.927***	3.122***
	CAD	1.079	1.675**	1.674**	3.861***	4.373***
	CHF	1.085	1.630*	2.981***	2.257**	1.839**
	EUR	1.676*	2.437***	1.230	3.833***	3.378***
	GBP	0.746	2.169**	3.314***	2.192**	1.859**
	JPY	0.378	1.597*	2.705***	2.355***	1.636*
	NOK	2.761***	2.320**	1.535*	2.769***	2.455***
	NZD	1.301	1.771**	1.499*	2.289**	2.270**
	SEK	2.045**	2.160**	1.993**	2.311**	2.907***
	SA	2.058**	2.265**	1.908**	3.444***	6.003***
	Panel	1.365	2.091**	2.476***	4.300***	4.823***
5-year horizon forecast (*h*=60)	AUD	-2.470	-0.571	1.805**	4.476***	3.822***
	CAD	1.043	0.343	-2.634	3.066***	3.986***
	CHF	0.936	1.676**	1.552*	2.756***	2.015**
	EUR	3.505***	3.004***	2.216**	7.981***	7.672***
	GBP	0.335	1.665**	1.554*	4.101***	4.453***
	JPY	1.056	2.199**	1.450*	3.918***	3.230***
	NOK	-0.255	1.697**	1.383*	2.087**	2.474***
	NZD	-0.907	1.263	1.065	3.830***	3.832***
	SEK	2.095**	3.401***	2.238**	1.988**	3.072***
	SA	0.523	0.952	0.879	2.957***	5.265***
	Panel	2.026**	3.292***	1.714**	5.018***	10.702***

Notes: * p<0.1, ** p<0.05, *** p<0.01 for two-sided test for the first column and one-sided test for the rest. Newey-West standard errors with *h*-1 lags are applied. In column (1), a positive value indicates the mean square error of univariate s_t is smaller than that of q_t. Panel regressions include country fixed effect. Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with *h*-1 lags in parentheses.

Table 12

Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} X_t + e_{t+h}$

	Independent variables	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
1-month horizon forecast (h=1)	s_t (simple average)	-0.02	0.00	0.02	0.03	0.09	0.13	0.20	0.20
	US treasury premium	-0.02	-0.01	0.00	0.04	0.07	0.08	0.17	0.18
	MAR global factor	-0.02	-0.01	0.02	0.05	0.07	0.08	0.11	0.12
	GZ spread	-0.02	-0.01	-0.01	0.00	0.03	0.06	0.15	0.17
	Log SP500	-0.02	0.00	0.04	0.08	0.10	0.13	0.22	0.24
	Log VIX	-0.02	-0.02	-0.01	0.01	0.05	0.06	0.09	0.11
	US Term spread (5y-FF)	-0.02	-0.01	0.00	0.03	0.08	0.09	0.12	0.15
	US Term spread (10y-2y)	-0.02	-0.02	-0.01	0.02	0.07	0.09	0.12	0.13
	TED	-0.02	-0.02	0.01	0.03	0.04	0.06	0.07	0.08
	Intermediary leverage	-0.02	-0.02	-0.01	0.02	0.06	0.08	0.10	0.11
	Interm. weighted return	-0.02	-0.01	-0.01	0.03	0.07	0.09	0.14	0.14
	Log Repo	-0.02	0.00	0.02	0.05	0.14	0.16	0.18	0.18
	Log Commercial Paper	-0.02	-0.02	-0.01	0.02	0.06	0.07	0.09	0.11
1-year horizon forecast (h=12)	s_t (simple average)	-0.02	0.17	0.50	0.57	0.64	0.70	0.82	0.83
	US treasury premium	-0.02	0.11	0.19	0.26	0.42	0.60	0.61	0.62
	MAR global factor	0.00	0.14	0.30	0.47	0.53	0.59	0.65	0.65
	GZ spread	-0.02	0.06	0.12	0.36	0.44	0.48	0.53	0.53
	Log SP500	-0.02	0.07	0.18	0.34	0.47	0.55	0.65	0.66
	Log VIX	-0.02	-0.01	0.13	0.27	0.39	0.40	0.43	0.44
	US Term spread (5y-FF)	-0.02	0.01	0.09	0.18	0.35	0.40	0.45	0.46
	US Term spread (10y-2y)	-0.02	0.01	0.07	0.26	0.44	0.65	0.72	0.73
	TED	-0.02	0.01	0.11	0.31	0.37	0.68	0.72	0.72
	Intermediary leverage	-0.02	0.00	0.04	0.13	0.37	0.48	0.57	0.58
	Interm. weighted return	-0.02	-0.02	-0.01	-0.01	0.01	0.06	0.11	0.13
	Log Repo	-0.02	0.00	0.04	0.23	0.31	0.33	0.35	0.36
	Log Commercial Paper	-0.02	0.02	0.08	0.25	0.35	0.38	0.42	0.42

Notes: Adjusted R^2 are reported. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 12 (continued)

Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} X_t + e_{t+h}$

	Independent variables	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
3-year horizon forecast (h=36)	s_t (simple average)	0.06	0.20	0.54	0.68	0.75	0.80	0.91	0.91
	US treasury premium	-0.02	0.03	0.12	0.34	0.42	0.46	0.49	0.50
	MAR global factor	-0.02	0.12	0.30	0.40	0.56	0.59	0.63	0.64
	GZ spread	-0.02	0.09	0.32	0.46	0.53	0.59	0.60	0.61
	Log SP500	-0.02	0.00	0.04	0.41	0.61	0.72	0.79	0.79
	Log VIX	-0.02	0.05	0.23	0.34	0.47	0.55	0.59	0.60
	US Term spread (5y-FF)	-0.02	0.09	0.21	0.28	0.50	0.54	0.58	0.59
	US Term spread (10y-2y)	-0.02	0.02	0.11	0.21	0.30	0.40	0.41	0.41
	TED	-0.02	0.01	0.07	0.17	0.21	0.22	0.25	0.25
	Intermediary leverage	-0.02	0.02	0.09	0.16	0.26	0.33	0.42	0.42
	Interm. weighted return	-0.02	0.00	0.01	0.02	0.06	0.09	0.13	0.17
	Log Repo	-0.02	-0.01	0.03	0.10	0.23	0.30	0.45	0.45
	Log Commercial Paper	-0.02	0.00	0.02	0.06	0.20	0.37	0.56	0.56
5-year horizon forecast (h=60)	s_t (simple average)	0.24	0.56	0.63	0.71	0.75	0.83	0.86	0.87
	UST premium	-0.02	0.00	0.07	0.23	0.50	0.57	0.60	0.61
	MAR global factor	-0.02	0.01	0.17	0.40	0.57	0.60	0.73	0.74
	GZ spread	-0.02	0.02	0.45	0.60	0.71	0.74	0.75	0.75
	Log SP500	-0.02	0.00	0.08	0.22	0.53	0.64	0.66	0.66
	Log VIX	-0.02	0.03	0.13	0.27	0.35	0.48	0.54	0.57
	Term spread (5y-FF)	-0.02	-0.01	0.03	0.16	0.20	0.23	0.28	0.30
	Term spread (10y-2y)	-0.02	0.00	0.02	0.19	0.40	0.41	0.44	0.50
	TED	-0.02	0.00	0.03	0.18	0.38	0.40	0.43	0.43
	Intermediary leverage	-0.02	0.00	0.04	0.11	0.20	0.29	0.30	0.31
	Interm. weighted return	-0.02	-0.01	-0.01	-0.01	0.03	0.06	0.13	0.15
	Log Repo	-0.02	-0.01	0.00	0.03	0.11	0.14	0.15	0.16
	Log Commercial Paper	-0.02	0.02	0.04	0.08	0.34	0.40	0.42	0.42

Notes: Adjusted R^2 are reported. Log SP500, Log Repo and Log Commercial Paper are log linearly detrended. MAR global factor is Miranda-Agrippino and Rey (2020) global factor. GZ spread is U.S. corporate bond credit spread taken from Gilchrist and Zakrajšek (2012). Intermediary leverage ratio and Intermediary weighted return are taken from He et al. (2017). TED is the 3-month Treasury Eurodollar spread. s_t reported here is the simple average exchange rate. Log SP500, Log Repo and Log Commercial Paper are linearly detrended.

Table 13
Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} q_t + e_{t+h}$

Currency	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
1-month horizon forecast								
AUD	-0.02	-0.01	0.00	0.03	0.07	0.09	0.17	0.20
CAD	-0.02	-0.01	0.02	0.04	0.07	0.12	0.20	0.23
CHF	-0.02	0.00	0.02	0.04	0.06	0.07	0.09	0.09
EUR	-0.02	-0.01	0.02	0.06	0.10	0.13	0.17	0.18
GBP	-0.02	-0.01	0.00	0.03	0.07	0.09	0.14	0.15
JPY	-0.02	-0.01	0.01	0.06	0.08	0.10	0.16	0.17
NOK	-0.02	-0.01	0.02	0.04	0.11	0.14	0.18	0.20
NZD	-0.02	0.00	0.02	0.04	0.08	0.10	0.17	0.22
SEK	-0.02	-0.01	0.01	0.04	0.07	0.08	0.13	0.19
SA	-0.02	-0.01	0.01	0.03	0.07	0.10	0.16	0.17
Panel	-0.02	0.00	0.01	0.02	0.05	0.06	0.10	0.10
1-year horizon forecast								
AUD	-0.02	0.14	0.34	0.51	0.58	0.65	0.73	0.73
CAD	-0.02	0.04	0.36	0.52	0.62	0.66	0.83	0.83
CHF	0.00	0.15	0.35	0.44	0.54	0.64	0.72	0.72
EUR	0.00	0.19	0.52	0.65	0.70	0.71	0.84	0.85
GBP	-0.02	0.18	0.26	0.47	0.57	0.64	0.81	0.82
JPY	-0.02	0.08	0.25	0.54	0.68	0.71	0.75	0.75
NOK	-0.02	0.09	0.45	0.61	0.74	0.77	0.79	0.79
NZD	-0.02	0.22	0.39	0.57	0.65	0.70	0.75	0.76
SEK	-0.02	0.10	0.47	0.62	0.67	0.73	0.75	0.75
SA	-0.02	0.10	0.44	0.56	0.67	0.73	0.75	0.76
Panel	0.04	0.15	0.36	0.42	0.52	0.56	0.64	0.64

Notes: SA is the regression with simple average of all nine currencies. Adjusted R^2 are reported. Panel regressions include country fixed effect.

Table 13 (continued)

Summary of rolling window R^2 of out-of-sample forecasting (5-year rolling window): $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} q_t + e_{t+h}$

Currency	min (1)	25%tile (2)	50%tile (3)	75%tile (4)	90%tile (5)	95%tile (6)	99%tile (7)	max (8)
3-year horizon forecast								
AUD	-0.02	0.20	0.51	0.76	0.85	0.87	0.87	0.87
CAD	-0.02	0.14	0.53	0.60	0.83	0.89	0.93	0.93
CHF	-0.02	0.12	0.33	0.58	0.85	0.89	0.90	0.90
EUR	-0.02	0.17	0.46	0.63	0.74	0.81	0.89	0.89
GBP	0.01	0.24	0.49	0.71	0.84	0.86	0.87	0.88
JPY	-0.01	0.25	0.55	0.82	0.91	0.95	0.97	0.97
NOK	-0.02	0.09	0.24	0.56	0.70	0.79	0.94	0.95
NZD	0.03	0.28	0.54	0.71	0.76	0.83	0.88	0.88
SEK	-0.02	0.06	0.30	0.63	0.77	0.79	0.82	0.82
SA	-0.02	0.11	0.43	0.71	0.77	0.82	0.89	0.89
Panel	0.23	0.40	0.53	0.63	0.71	0.74	0.82	0.82
5-year horizon forecast								
AUD	0.06	0.48	0.62	0.89	0.92	0.94	0.95	0.95
CAD	0.25	0.46	0.54	0.66	0.74	0.83	0.87	0.87
CHF	0.11	0.53	0.61	0.68	0.74	0.83	0.87	0.88
EUR	0.05	0.22	0.58	0.68	0.73	0.74	0.77	0.81
GBP	0.46	0.64	0.71	0.82	0.90	0.90	0.91	0.91
JPY	0.21	0.36	0.58	0.76	0.86	0.89	0.92	0.93
NOK	0.07	0.34	0.47	0.53	0.60	0.62	0.65	0.66
NZD	0.04	0.64	0.76	0.86	0.89	0.90	0.90	0.90
SEK	0.03	0.31	0.54	0.64	0.72	0.80	0.83	0.83
SA	0.30	0.61	0.67	0.71	0.74	0.78	0.82	0.82
Panel	0.60	0.66	0.68	0.71	0.75	0.76	0.77	0.78

Notes: SA is the regression with simple average of all nine currencies. Adjusted R^2 are reported. Panel regressions include country fixed effect.

Table 14

Regression statistics of in sample forecasting using simulated data: $s_{t+h} - s_t = \alpha + \beta s_t + e_{t+h}$

	Beta			t-stat			Adjusted R^2		
	Actual data	MC *p*-value	BS *p*-value	Actual data	MC *p*-value	BS *p*-value	Actual data	MC *p*-value	BS *p*-value
Currency	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-month horizon forecast (*h*=1)									
AUD	-0.016	0.52	0.52	-1.41	0.57	0.58	0.004	0.57	0.57
CAD	-0.017	0.50	0.50	-1.69	0.44	0.44	0.006	0.50	0.51
CHF	-0.011	0.67	0.69	-1.19	0.66	0.68	0.002	0.65	0.67
EUR	-0.019	0.45	0.45	-1.41	0.57	0.57	0.005	0.52	0.52
GBP	-0.013	0.63	0.62	-1.11	0.71	0.71	0.000	0.74	0.73
JPY	-0.023	0.35	0.36	-1.73	0.42	0.42	0.008	0.41	0.41
NOK	-0.008	0.78	0.77	-0.66	0.86	0.84	-0.002	0.86	0.85
NZD	-0.020	0.43	0.44	-1.64	0.46	0.47	0.007	0.45	0.46
SEK	-0.018	0.48	0.49	-1.48	0.54	0.56	0.003	0.62	0.63
SA	-0.014	0.60	0.80	-1.28	0.64	0.63	0.003	0.64	0.74
Panel	-0.015	0.47	0.48	-1.91	0.65	0.64	0.003	0.84	0.84
1-year horizon forecast (*h*=12)									
AUD	-0.224	0.45	0.44	-2.03	0.57	0.56	0.113	0.49	0.49
CAD	-0.191	0.53	0.52	-2.11	0.54	0.53	0.111	0.50	0.50
CHF	-0.123	0.70	0.71	-1.66	0.67	0.68	0.084	0.60	0.60
EUR	-0.257	0.37	0.36	-2.18	0.50	0.51	0.131	0.42	0.41
GBP	-0.216	0.46	0.46	-1.40	0.74	0.75	0.075	0.64	0.64
JPY	-0.283	0.31	0.32	-2.02	0.57	0.57	0.143	0.38	0.37
NOK	-0.193	0.52	0.52	-1.73	0.66	0.66	0.073	0.65	0.65
NZD	-0.252	0.39	0.40	-1.95	0.60	0.60	0.139	0.40	0.41
SEK	-0.301	0.29	0.29	-2.14	0.53	0.54	0.127	0.44	0.45
SA	-0.219	0.45	0.46	-1.92	0.60	0.63	0.111	0.49	0.46
Panel	-0.217	0.30	0.30	-2.39	0.70	0.69	0.110	0.37	0.37

Notes: SA is the regression with simple average of all nine currencies. MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Inference are based on Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with *h*-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. The panel regressions are with country fixed effects. *p*-values of one-sided test are reported.

Table 14 (continued)

Regression statistics of in sample forecasting using simulated data: $s_{t+h} - s_t = \alpha + \beta s_t + e_{t+h}$

	Beta			t-stat			Adjusted R^2		
Currency	Actual data (1)	MC *p*-value (2)	BS *p*-value (3)	Actual data (4)	MC *p*-value (5)	BS *p*-value (6)	Actual data (7)	MC *p*-value (8)	BS *p*-value (9)
3-year horizon forecast (*h*=36)									
AUD	-0.672	0.39	0.39	-4.75	0.26	0.26	0.45	0.29	0.28
CAD	-0.622	0.45	0.44	-3.06	0.52	0.50	0.40	0.37	0.37
CHF	-0.404	0.66	0.67	-5.09	0.21	0.22	0.48	0.24	0.24
EUR	-0.733	0.33	0.34	-5.13	0.22	0.21	0.52	0.19	0.18
GBP	-0.618	0.45	0.46	-2.08	0.70	0.71	0.22	0.66	0.66
JPY	-0.946	0.16	0.15	-4.78	0.25	0.24	0.49	0.22	0.22
NOK	-0.652	0.42	0.42	-2.72	0.58	0.58	0.33	0.49	0.49
NZD	-0.712	0.35	0.37	-5.90	0.15	0.16	0.57	0.12	0.13
SEK	-0.764	0.32	0.31	-3.71	0.41	0.40	0.42	0.35	0.35
SA	-0.689	0.37	0.37	-4.07	0.34	0.34	0.48	0.25	0.21
Panel	-0.657	0.20	0.21	-5.26	0.31	0.31	0.42	0.11	0.11
5-year horizon forecast (*h*=60)									
AUD	-1.030	0.35	0.36	-7.48	0.20	0.19	0.73	0.12	0.12
CAD	-1.125	0.28	0.26	-6.31	0.28	0.27	0.73	0.12	0.11
CHF	-0.606	0.66	0.67	-6.10	0.28	0.29	0.71	0.14	0.15
EUR	-1.122	0.27	0.28	-10.72	0.08	0.08	0.78	0.07	0.07
GBP	-1.25	0.17	0.17	-3.65	0.58	0.58	0.44	0.56	0.55
JPY	-1.283	0.15	0.14	-4.89	0.43	0.42	0.68	0.19	0.19
NOK	-1.262	0.16	0.16	-5.81	0.31	0.31	0.60	0.31	0.32
NZD	-0.964	0.40	0.41	-13.13	0.04	0.05	0.82	0.04	0.04
SEK	-1.244	0.18	0.18	-7.16	0.22	0.22	0.69	0.17	0.18
SA	-1.111	0.29	0.28	-7.33	0.20	0.20	0.76	0.09	0.06
Panel	-1.030	0.14	0.14	-10.67	0.11	0.11	0.66	0.05	0.05

Notes: SA is the regression with simple average of all nine currencies. MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Inference are based on Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with *h*-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. The panel regressions are with country fixed effects. *p*-values of one-sided test are reported.

Table 15

5-year rolling window out-of-sample prediction error with simulated data:

$\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model)

		CW statistics				CW statistics		
			MC	BS			MC	BS
		Actual data	*p*-value	*p*-value		Actual data	*p*-value	*p*-value
Currency		(1)	(2)	(3)		(4)	(5)	(6)
AUD		-1.07	0.84	0.83		2.93	0.55	0.54
CAD		-0.13	0.50	0.50		3.86	0.24	0.24
CHF		-0.02	0.46	0.47		2.26	0.82	0.82
EUR	1-month	0.04	0.43	0.43	3-year	3.83	0.23	0.25
GBP	horizon	-1.50	0.92	0.91	horizon	2.19	0.85	0.85
JPY	forecast	-0.90	0.78	0.79	forecast	2.36	0.79	0.79
NOK	(h=1)	-1.36	0.90	0.90	(h=36)	2.77	0.62	0.61
NZD		-0.44	0.64	0.63		2.29	0.82	0.80
SEK		-0.68	0.72	0.72		2.31	0.80	0.81
SA		-0.98	0.81	0.80		3.44	0.36	0.36
Panel		-0.49	0.66	0.66		4.30	0.57	0.55
AUD		1.29	0.94	0.93		4.48	0.20	0.21
CAD		2.90	0.30	0.29		3.07	0.48	0.47
CHF		2.81	0.33	0.33		2.76	0.59	0.58
EUR	1-year	3.98	0.05	0.05	5-year	7.98	0.03	0.03
GBP	horizon	2.28	0.60	0.59	horizon	4.10	0.25	0.26
JPY	forecast	1.84	0.80	0.80	forecast	3.92	0.29	0.28
NOK	(h=12)	2.50	0.48	0.47	(h=60)	2.09	0.84	0.84
NZD		1.69	0.85	0.84		3.83	0.30	0.30
SEK		2.10	0.68	0.67		1.99	0.87	0.87
SA		1.85	0.79	0.79		2.96	0.51	0.51
Panel		2.00	0.93	0.92		5.02	0.44	0.44

Notes: SA is the regression with simple average of all nine currencies. MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Inference are based on Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. The panel regressions are with country fixed effects. *p*-values of one-sided test are reported.

Table 16

5-year rolling window R^2 of out of sample forecasting with simulated data from the regression: $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_{t+h}$

Currency		90%tile of rolling R^2 Actual data (1)	MC p-value (2)	BS p-value (3)	95%tile of rolling R^2 Actual data (4)	MC p-value (5)	BS p-value (6)
AUD	1-month horizon forecast (h=1)	0.08	0.51	0.50	0.10	0.50	0.48
CAD		0.07	0.69	0.68	0.15	0.92	0.91
CHF		0.13	0.07	0.07	0.21	0.99	0.99
EUR		0.10	0.25	0.24	0.13	0.82	0.81
GBP		0.10	0.25	0.24	0.14	0.87	0.87
JPY		0.06	0.82	0.84	0.08	0.21	0.20
NOK		0.13	0.06	0.07	0.15	0.92	0.91
NZD		0.10	0.24	0.23	0.12	0.74	0.73
SEK		0.08	0.51	0.51	0.09	0.35	0.35
SA		0.09	0.37	0.37	0.13	0.80	0.80
Panel		0.06	0.12	0.13	0.09	0.01	0.01
AUD	1-year horizon forecast (h=12)	0.64	0.41	0.42	0.70	0.39	0.41
CAD		0.66	0.31	0.32	0.72	0.31	0.34
CHF		0.70	0.14	0.15	0.78	0.08	0.09
EUR		0.71	0.11	0.11	0.74	0.21	0.21
GBP		0.76	0.02	0.03	0.79	0.06	0.07
JPY		0.68	0.21	0.22	0.72	0.30	0.30
NOK		0.75	0.03	0.04	0.79	0.05	0.07
NZD		0.71	0.10	0.11	0.72	0.29	0.31
SEK		0.64	0.40	0.41	0.66	0.60	0.60
SA		0.64	0.41	0.42	0.70	0.40	0.41
Panel		0.57	0.09	0.10	0.62	0.09	0.12

Notes: SA is the regression with simple average of all nine currencies. MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Inference are based on Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. The panel regressions are with country fixed effects. p-values of one-sided test are reported.

Table 16 (continued)

5-year rolling window R^2 of out of sample forecasting with simulated data from the regression: $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_{t+h}$

Currency		90%tile of rolling R^2 Actual data (1)	90%tile of rolling R^2 MC *p*-value (2)	90%tile of rolling R^2 BS *p*-value (3)	95%tile of rolling R^2 Actual data (4)	95%tile of rolling R^2 MC *p*-value (5)	95%tile of rolling R^2 BS *p*-value (6)
AUD	3-year horizon forecast (h=36)	0.83	0.65	0.68	0.85	0.69	0.72
CAD		0.77	0.84	0.84	0.83	0.78	0.78
CHF		0.83	0.66	0.66	0.85	0.70	0.71
EUR		0.71	0.93	0.94	0.81	0.84	0.84
GBP		0.91	0.21	0.23	0.93	0.22	0.23
JPY		0.91	0.21	0.22	0.95	0.09	0.10
NOK		0.71	0.93	0.93	0.81	0.83	0.83
NZD		0.81	0.72	0.74	0.84	0.74	0.75
SEK		0.71	0.93	0.93	0.73	0.95	0.95
SA		0.75	0.88	0.88	0.80	0.86	0.86
Panel		0.78	0.67	0.68	0.81	0.59	0.61
AUD	5-year horizon forecast (h=60)	0.83	0.63	0.66	0.91	0.37	0.41
CAD		0.75	0.82	0.84	0.82	0.75	0.77
CHF		0.95	0.09	0.09	0.95	0.13	0.14
EUR		0.80	0.73	0.74	0.81	0.79	0.80
GBP		0.93	0.19	0.19	0.94	0.20	0.20
JPY		0.96	0.05	0.05	0.96	0.08	0.08
NOK		0.67	0.93	0.93	0.73	0.92	0.92
NZD		0.85	0.57	0.57	0.89	0.50	0.49
SEK		0.76	0.81	0.82	0.78	0.85	0.85
SA		0.75	0.84	0.84	0.83	0.74	0.75
Panel		0.82	0.82	0.82	0.84	0.78	0.78

Notes: SA is the regression with simple average of all nine currencies. MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Inference are based on Newey-West standard errors and Driscoll Kraay (1998) standard errors (for panel regression) with h-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. The panel regressions are with country fixed effects. *p*-values of one-sided test are reported.

Table 17. Forecasts using GZ

Data generating process of the simulation (under the null hypothesis): $s_t - s_{t-1} = u_{1,t}$ and $GZ_t = \beta_1 s_{t-1} + \delta_1 GZ_{t-1} + \beta_2 s_{t-2} + \delta_2 GZ_{t-2} + u_{2,t}$

Regression statistics of in sample forecasting using simulated data: $s_{t+h} - s_t = \alpha + \beta GZ_t + e_{t+h}$

Simple average exchange rate	Beta: Actual data (1)	Beta: MC 2-sided p-value (2)	t-stat: Actual data (3)	t-stat: MC 2-sided p-value (4)	Adjusted R^2: Actual data (5)	Adjusted R^2: MC 1-sided p-value (6)
h=1	0.0003	0.76	0.40	0.96	-0.003	0.63
h=12	0.011	0.12	2.54	0.16	0.086	0.14
h=36	0.027	0.10	2.59	0.30	0.194	0.13
h=60	0.022	0.44	1.49	0.84	0.071	0.46

5-year rolling window out-of-sample prediction error with simulated data:

$\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^s_{t-61,t-1} GZ_t$ and $\widehat{s_{t+h} - s_t} = 0$ (GZ_t v.s. random walk model)

Simple average exchange rate	CW Statistics: Actual Data (1)	CW Statistics: MC 1-sided p-value (2)
h=1	0.51	0.26
h=12	1.52	0.55
h=36	3.41	0.07
h=60	2.01	0.56

5-year rolling window R^2 of out of sample forecasting with simulated data from the regression: $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} GZ_t + e_{t+h}$

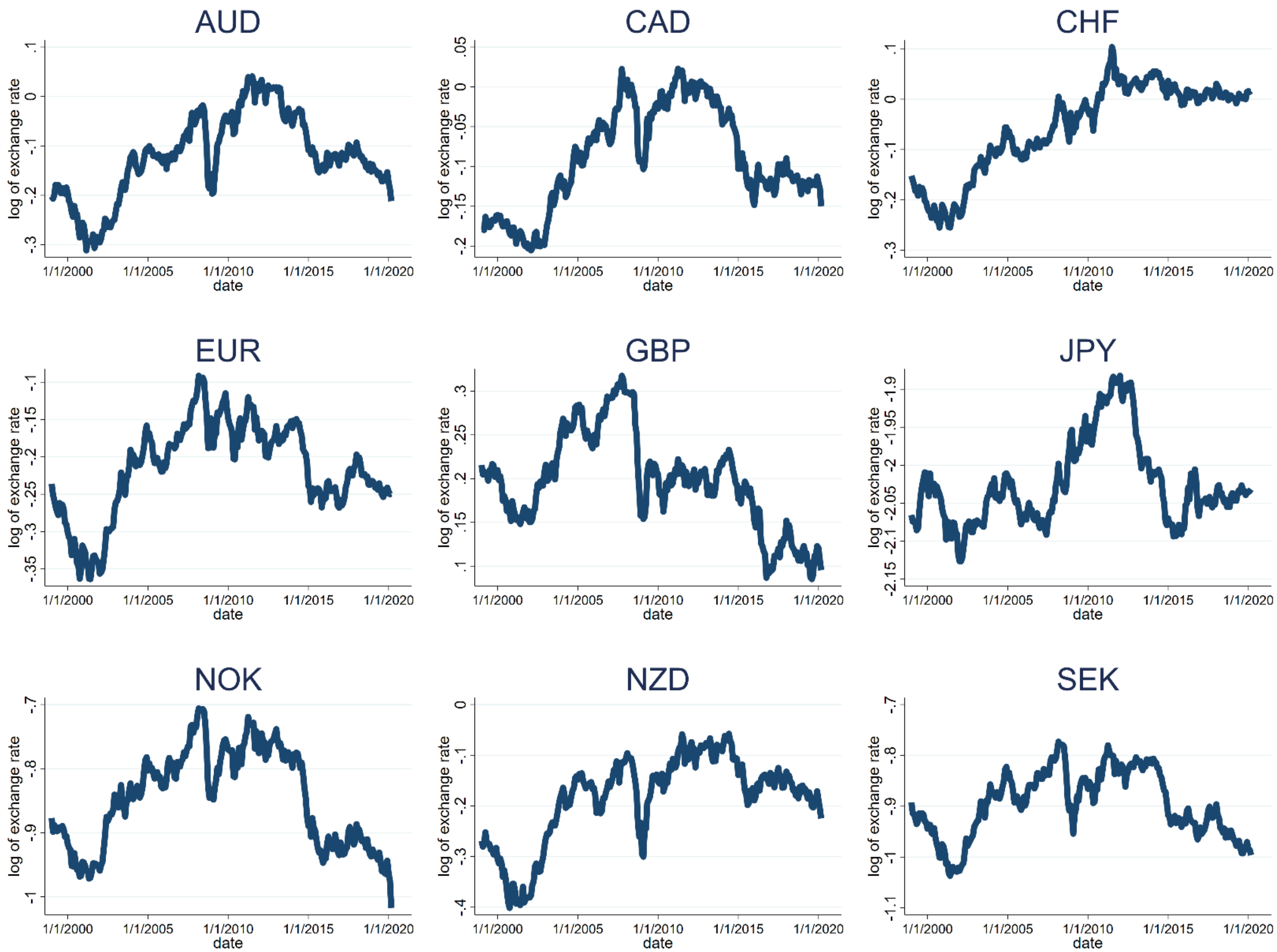
Simple average exchange rate	90%tile of rolling R^2: Actual data (1)	90%tile of rolling R^2: MC 1-sided p-value (2)	95%tile of rolling R^2: Actual data (3)	95%tile of rolling R^2: MC 1-sided p-value (4)
h=1	0.03	0.41	0.06	0.29
h=12	0.44	0.21	0.48	0.27
h=36	0.53	0.36	0.59	0.38
h=60	0.71	0.10	0.74	0.12

Notes: Each exercise simulates the data 5000 times using Monte Carlo. Newey-West standard errors with h-1 lags are used. p-values of two-sided test are reported for beta and t-statistics. p-values of one-sided test are reported for R^2 and CW statistics. The simulated data are simulated with empirically estimated coefficient and variance-covariance matrix. Kilian (1998) method is applied for correcting small sample bias. Number of lags (2) under the null hypothesis is chosen by AIC.

Figure 1

U.S. Dollar Exchange Rates 1999M1-2020M3

(log of U.S. dollar per unit of foreign currency)



Appendix 1: Data Appendix

Appendix Table 1: Data source

Variable	Data source	Sample period
Exchange rates	FRED	1999M1-2020M3 (end of month)
US treasury premium	Engel and Wu (2020) https://www.ssc.wisc.edu/~cengel/Data/LiquidityYield/	1999M1-2018M1
MAR global factor	Miranda-Agrippino and Rey (2020) (http://www.helenerey.eu/RP.aspx?pid=Published-Papers_en-GB&aid=291587444_67186463733)	1999M1-2019M4
GZ spread	Gilchrist and Zakrajsek (2012) https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html	1999M1-2020M3
Log SP500*	FRED	1999M1-2020M3
Log VIX	FRED	1999M1-2020M3
US Term spread (5y-FF)	FRED	1999M1-2020M3
US Term spread (10y-2y)	FRED	1999M1-2020M3
TED	FRED	1999M1-2020M3
Intermediary leverage	He, Kelly, Manela (2017) http://apps.olin.wustl.edu/faculty/manela/data.html	1999M1-2018M11
Intermediary weighted return	He, Kelly, Manela (2017) http://apps.olin.wustl.edu/faculty/manela/data.html	1999M1-2018M11
Log Repo*	Board of Governors of the Federal Reserve System	1999M8-2020M3
Log Commercial Paper*	Board of Governors of the Federal Reserve System	2001M1-2020M3
CPI Index	IMF IFS	1999M1-2020M3

Notes: * We linearly detrended the data. For in sample forecasting, we detrended the variable using the whole sample. For out-of-sample forecasting, we detrended the variable using the 60 observations within the window.

Appendix Table 2: Persistence of global risk variables

AR(1) coefficient from the regression $X_t = \alpha + \beta X_{t-1} + e_t$

Variable	AR(1) coefficient	Standard errors*	Obs #
MAR global factor	0.97	(0.02)	243
GZ spread	0.96	(0.05)	254
Log SP500	0.98	(0.02)	254
Log VIX	0.85	(0.03)	254
US Term spread (5y-FF)	0.90	(0.03)	254
US Term spread (10y-2y)	0.98	(0.01)	254
TED	0.84	(0.04)	254
Intermediary leverage	0.98	(0.01)	238
Intermediary weighted return	0.17	(0.10)	238
Log Repo	0.98	(0.01)	247
Log Commercial Paper	0.93	(0.03)	230

Notes: *Newey West standard errors with 5 lags are reported

AR(1) coefficient from the regression $X_t = \alpha + \beta X_{t-1} + e_t$ by currency

	Real exchange rate			US Treasury premium		
Currency	AR(1) coefficient	Standard errors*	Obs #	AR(1) coefficient	standard errors*	Obs #
AUD	0.99	(0.01)	254	0.78	(0.05)	228
CAD	0.98	(0.01)	254	0.90	(0.05)	228
CHF	0.97	(0.01)	254	0.82	(0.05)	228
EUR	0.98	(0.01)	254	0.82	(0.04)	228
GBP	0.97	(0.01)	254	0.72	(0.09)	228
JPY	0.99	(0.01)	254	0.81	(0.07)	228
NOK	0.98	(0.02)	254	0.84	(0.04)	228
NZD	0.98	(0.01)	254	0.78	(0.05)	228
SEK	0.99	(0.01)	254	0.85	(0.03)	228
Simple average	0.99	(0.01)	254	0.84	(0.04)	228

Notes: *Newey West standard errors with 5 lags are reported

Appendix 2: Simulation Methods

First we describe the simulation methods for the in-sample forecasts (Table 14), then for the out-of-sample exercises in Tables 15 and 16.

Data

For any given currency, we have data running from January 1999 to March 2020, for 255 data points. Let January 1999 be date $t=1$. T=255.

In-sample

For h=1,12,36,60, we estimate

(7) $s_{t+h} - s_t = a + b\, s_t + u_{t+h}$

We then calculate the $\hat{b}$ and the t-statistics of $\hat{b}$ using Newey-West standard error of $h-1$ lags.

For the panel specification, we estimate

$s_{i,t+h} - s_{i,t} = a_i + b s_{i,t} + u_{i,t+h}$

We then calculate the $\hat{b}_i$ and the *t*-statistics of $\hat{b}_i$ using Driscoll-Kraay standard error of $h-1$ lags.

Also, we record the adjusted R^2 for $h = 1, 12, 36, 60$.

Out-of-sample

For h=1,12,36,60, we use 60 data points to estimate

(8) $s_{t+h} - s_t = a_{h,t} + b_{h,t} s_t + u_{t+h}$

for $t = 1, \ldots, T-h$. That is, we run rolling regressions with 60 observations each.

We forecast h periods ahead using the formula

$\tilde{s}_{t+1+h} - s_{t+1} = \hat{a}_{h,t} + \hat{b}_{h,t} s_{t+1} + \hat{u}_{t+h}$

for $t = 1, \ldots, T-h$, where the ^ over variables refers to the estimated values, and $\tilde{s}_{t+1+i}$ is the forecasted value. That is, for $h = 1, 12, 36, 60$, we make h-period ahead forecasts.

We then calculate the $T-60-h$ forecast errors, $\tilde{s}_{t+1+h} - s_{t+1+h}$, and calculate their mean-squared error. We use the Clark-West statistic to compare that m.s.e. to the m.s.e. of the forecast of no change in the exchange rate, for which the forecast error is $s_{t+1+h} - s_{t+1}$. We use Newey-West standard error of $h-1$ lags to correct for the Clark-West statistics.

For the panel specification, we forecast h periods ahead using the following formula and apply the same procedure above

$$\tilde{s}_{i,t+1+h} - s_{i,t+1} = \hat{a}_{i,h,t} + \hat{b}_{h,t} s_{i,t+1} + \hat{u}_{i,t+h}$$

We use Driscoll-Kraay standard error of $h-1$ lags to correct for the panel Clark-West statistics.

Also, we record the $T-60-h$ values of adjusted R^2 and record the min, max, 50^{th}, 90^{th}, 95^{th}, and 99^{th} percentile of those $T-60-h$ regressions for $h = 1, 12, 36, 60$.

Monte Carlo

We perform $K = 5000$ iterations of the following procedure:

In iteration *k*, $k = 1, \ldots, K$, we create an artificial time series that has $2000+T$ elements as follows:

Under the null of a zero-drift random walk, we calculate the variance of $s_{t+1} - s_t$ for the sample of $T-1$ observations of $s_{t+1} - s_t$. We then construct an artificial time series of $2000+T-1$ random variables drawing from a normal distribution with mean zero and variance equal to the sample variance of $s_{t+1} - s_t$. Call each of these ε_j, $j = 1, \ldots, 2000+T-1$. Then we construct a series of length $2000+T$ with the following properties: The first element, call it x_1 is equal to zero. Then for $j = 1, \ldots, 2000+T-1$, we have $x_{j+1} = x_j + \varepsilon_j$. Now take the last T values of x_j. Call these $\dot{s}_t$ for $t = 1, \ldots, T$, which is the simulated exchange rate series for iteration *k*.

For the panel specification, under the null of a zero-drift random walk, we calculate the variance covariance matrix of $s_{i,t+1} - s_{i,t}$ for the sample of $T-1$ observations of $s_{i,t+1} - s_{i,t}$ where *i* is the index of a currency ($i=\{1,2...I\}$). We then construct an artificial time series of $(2000+T-1)\times I$ random variables drawing from a multivariate normal distribution with mean zero and variance and covariance equal to the sample variance covariance of $s_{i,t+1} - s_{i,t}$. Call each of these $\varepsilon_{i,j}$, $j = 1, \ldots, 2000+T-1$. Then we construct a series of length $2000+T$ with the following properties: The first element, call it $x_{i,1}$ is equal to zero. Then for $j = 1, \ldots, 2000+T-1$

, we have $x_{i,j+1} = x_{i,j} + \varepsilon_{i,j}$. Now take the last *T* values of $x_{i,j}$. Call these $\dot{s}_{i,t}$ for $t = 1, \ldots, T$, which is the simulated panel exchange rate series for iteration *k*.

Next proceed exactly as in the Data section, but use $\dot{s}_t$ as the "data" rather than s_t.

So in each iteration *k*, for in-sample, we record a coefficient estimate $\hat{b}$, t-statistic of $\hat{b}$ and adjusted R^2. For out-of-sample, we record a Clark-West statistic and adjusted R^2 for the min, max, 50th, 90th, 95th, and 99th percentile of those $T-60-h$ rolling regressions.

Repeat this *K* times so we have the Monte Carlo distribution of these statistics.

Boostrap (with replacement)

We essentially follow the same steps as above for the Monte Carlo, but the creation of the artificial data is different.

We perform $K = 5000$ iterations of the following procedure:

In iteration *k*, $k = 1, \ldots, K$, we create an artificial time series that has $2000+T$ elements as follows:

Under the null of a zero-drift random walk, we collect the $T-1$ observations of $s_{t+1} - s_t$. We then use a random number generator that chooses a value from 1 to $T-1$ with equal probability. We construct an artificial time series of $2000+T-1$ random variables, calling each element of this series ε_j, $j = 1, \ldots, 2000+T-1$. ε_j is created as follows: For each *j*, we use the random number generator to choose a numeral *n* with equal probability, and then we set ε_j to be the *n*th element of $s_{t+1} - s_t$ Then we construct a series of length $2000+T$ with the following properties: The first element, call it x_1 is equal to zero. Then for $j = 1, \ldots, 2000+T-1$, we have $x_{j+1} = x_j + \varepsilon_j$. Now take the last *T* values of x_j. Call these $\ddot{s}_t$ for $t = 1, \ldots, T$, which is the simulated exchange rate series for iteration *k*.

For the panel specification, under the null of a zero-drift random walk, we collect $T-1$ observations of $s_{i,t+1} - s_{i,t}$, where *i* is the index of a currency (*i={1,2...I}*) and for each *t* there are *I*-tuple of exchange rates. We use a random number generator that chooses an *I*-tuple from 1 to $T-1$ with equal probability. We construct an artificial time series of $(2000+T-1)\times I$ random variables, calling each element of this series $\varepsilon_{i,j}$, $j = 1, \ldots, 2000 + T - 1$. $\varepsilon_{i,j}$ is created as follows: For each *j*, we use the random number generator to choose a numeral *n* with equal probability, and then we set each element in ε_j to be the *n*th tuple of $s_{i,t+1} - s_{i,t}$. Then we construct a series of length $2000 + T$ with the following properties: The first *I*-tuple, call it $x_{i,1}$ is equal to zero. Then for $j = 1, \ldots, 2000 + T - 1$, we have $x_{i,j+1} = x_{i,j} + \varepsilon_{i,j}$. Now take the last *T* values of $x_{i,j}$. Call these $\dot{s}_{i,t}$ for $t = 1, \ldots, T$, which is the simulated panel exchange rate series for iteration *k*.

Next proceed exactly as in the Data section, but use $\dot{s}_t$ as the "data" rather than s_t.

So in each iteration *k*, for in-sample, we record a coefficient estimate $\hat{b}$, t-statistic of $\hat{b}$ and adjusted R^2. For out-of-sample, we record a Clark-West statistic and adjusted R^2 for the min, max, 50th, 90th, 95th, and 99th percentile of those $T - 60 - h$ rolling regressions.

Repeat this *K* times so we have the bootstrap distribution of these statistics.

Appendix 3: Additional notes to the tables

Table 1:

The regression is in sample: $s_{t+h} - s_t = \alpha + \beta s_t + e_t$

Single country

Parameters estimated by OLS, Newey-West standard errors of *h*-1 lags in parentheses. Significance inference is based on Phillips Perron test statistics and compared to the Dickey Fuller distribution.

Panel

The panel allows for country fixed effect.

Parameter are estimated by OLS, the standard errors are Driscoll Kraay (1998) standard errors with h-1 lags in parentheses.

Significance inference is based on Choi (2001), which is a panel version of Phillips Perron test statistics and compared to inverse chi square distribution.

Table 2:

The regression is out of sample rolling regression, rolling window is 5 year: $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_t$ vs a random walk model

The Clark West statistics is calculated as follows:

A positive statistic indicates the larger model is the better one in the Clark West sense.

The squared regression error is obtained for each prediction,

$f_{1,t} = (y_t - \hat{y}_{1,t})^2$, $f_{2,t} = (y_t - \hat{y}_{2,t})^2$ and $adj = (\hat{y}_{1,t} - \hat{y}_{2,t})^2$

For each period, we compute: $\hat{f}_t = f_{1,t} - (f_{2,t} - adj)$

We regress $\hat{f}_t$ on a constant and test if the constant is significantly bigger than zero (one-sided test). (Clark West 2007) The inference is based on usual t-statistics of the constant term. We use Newey West standard errors for accounting serial correlation in the Clark West test.

Panel

The panel allows for country fixed effect.

We use Driscoll Kraay (1998) for accounting serial correlation in the Clark West test.

For the Clark West statistics, we still regress on one single constant, (i.e. no country specific constant) Significance is based on one-sided test.

Table 3:

Table 3 uses the regressions of table 2, but reports the adjusted R^2 of the regressions.

Table 4:

Table 4 does three in-sample regressions:

$s_{t+h} - s_t = \alpha + \beta^X X_t + e_t$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_t$ and $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{ss} s_t + e_t$

Parameters estimated by OLS with Newey-West standard errors of h-1 lags.

Inference of significance for s_t is based on Phillips Perron test statistics and compare to the Dickey Fuller distribution

Significance inference for macro variable is based on usual t statistics.

Table 4 reports only regression with simple average of exchange rates.

Table 5:

Table 5 does the same regressions as Table 4, but summarizes the count of all 9 countries at 5% significance level.

Inference of significance for s_t is based on Phillips Perron test statistics and compare to the Dickey Fuller distribution

Significance inference for macro variable is based on usual t statistics.

Table 6

The same inference as Table 1, but replacing the RHS variable with q_t.

The regression is in-sample: $s_{t+h} - s_t = \alpha + \beta q_t + e_{t+h}$

Table 7

Table 7 does the same inference as in Table 4, and treats q_t as a "macro variable"

Table 7 does three in-sample regressions:

$s_{t+h} - s_t = \alpha + \beta^X X_t + e_t$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_t$ and $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{ss} s_t + e_t$

Parameters estimated by OLS with Newey-West standard errors of h-1 lags.

Significance inference for s_t is based on Phillips Perron test statistics and compare to the Dickey Fuller distribution.

Significance inference for q_t is based on usual *t* statistics in the bivariate regression (column 5-7).

Significance inference for q_t is based on Phillips Perron test statistics and compared to the Dickey Fuller distribution in the univariate regression (column 3-4).

Table 8:

The regression is out-of-sample rolling regression, rolling window is 5 year, compared across 5 models. The first comparison involves two non-nested model, for which we compare MSPE of: model1 based on X_t minus model 2 based on s_t. Therefore, a positive statistic means the MSPE is larger for X_t than s_t. We use the Diebold Mariano statistics. The significance stars are based on a two-sided test.

i) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Univariate s_t vs univariate X_t) (Diebold Mariano West test)

The rest of the tests involve nested model comparisons, we applied the Clark West statistics. The significance stars are based on one-sided tests. A positive statistic indicates the larger model is better in Clark West sense.

ii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ (Bivariate v.s. univariate X_t) (Clark West test)

iii) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{XX}_{t-61,t-1} X_t + \hat{\beta}^{ss}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ (Bivariate v.s. univariate s_t) (Clark West test)

iv) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{s}_{t-61,t-1} s_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate s_t v.s. random walk model (r.w.) (Clark West test)

v) $\widehat{s_{t+h} - s_t} = \hat{\alpha} + \hat{\beta}^{X}_{t-61,t-1} X_t$ and $\widehat{s_{t+h} - s_t} = 0$ (Univariate X_t v.s. random walk model (r.w.)) (Clark West test)

The Clark West statistics is computed based on the procedure described in Table 2:

Table 9:

Table 9 does the same regression as Table 8, but summarizes the count of all 9 countries.

We count the countries below 5% significant level. The inference is based on usual t-statistics of the constant term. We use Newey West for accounting for serial correlation in the Clark West test.

Table 10

The same inference as Table 2, but replacing the RHS variable with q_t .

Table 11

Table 11 uses the same inference as in Table 8, but treats q_t as a new "macro variable"

Table 12:

The regression is out of sample rolling regression, rolling window is 5 year,

$$s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} X_t + e_t$$

We reported the adjusted R^2 of the simple average exchange rate case.

Table 13

The same inference as Table 12, but replacing the RHS variable with q_t .

Tables 14-16 are simulated data regressions

The simulation procedures are described in Appendix 2: Simulation Methods.

Table 14

The regression is in sample: $s_{t+h} - s_t = \alpha + \beta s_t + e_t$

We report the beta, *t* statistics and adjusted R2.

Single country

The data are simulated with no drift

Parameters are estimated by OLS, the standard errors and *t* statistics are based on Newey-West standard errors with *h*-1 lags in parentheses.

Restricted Panel

The panel are simulated with no drift, but simulated with cross country covariance matrix

We regress restricting the slope coefficients to be the same. Parameters are estimated by OLS, the standard errors are Driscoll Kraay (1998) standard errors with *h*-1 lags in parentheses.

Table 15

The regression is out of sample: $s_{t+h} - s_t = \alpha + \beta_{t-61,t-1} s_t + e_t$ vs random walk

Single country

Parameters are estimated by OLS, the standard errors are Newey West standard errors with *h*-1 lags in parentheses.

Restricted Panel

We regress restricting the beta coefficient to be the same. Parameters are estimated by OLS, the standard errors are Driscoll Kraay (1998) standard errors with *h*-1 lags in parentheses.
Then we calculate the Clark West statistics based on the prediction of this regression.

The test statistics are calculated as in Table 2.

Table 16

Table 16 has the same regression as table 15. We report the adjusted R^2 from the data (Actual data column) and compare with the simulation.

Table 17

We first estimate two equations from the actual data:

$$s_t - s_{t-1} = u_{1,t}$$

$$GZ_t = \alpha + \beta_1 GZ_{t-1} + \beta_2 GZ_{t-2} + \delta_1 s_{t-1} + \delta_2 s_{t-2} + u_{2,t}$$

We correct for the bias using Kilian (1998) method. We compute the empirically estimated coefficients ($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$ and $\hat{\delta}_2$) and variance covariance matrix of the error terms. We use these parameter estimates to simulate the series $\dot{s}_t$ and $G\dot{Z}_t$ with empirical sample size (*T*) 5000 times using a Monte Carlo method. Within each simulation *k*, we re-estimate β_1, β_2, δ_1 and δ_2. Call it $\tilde{\beta}_{1,k}$, $\tilde{\beta}_{2,k}$, $\tilde{\delta}_{1,k}$ and $\tilde{\delta}_{2,k}$. We then take average of these estimates across simulation, i.e. $\tilde{\beta}_1 = \frac{\sum_{k=1}^{5000} \tilde{\beta}_{1,k}}{5000}$. Our empirical estimates of the bias are $\tilde{\beta}_1 - \hat{\beta}_1, \tilde{\beta}_2 - \hat{\beta}_2, \tilde{\delta}_1 - \hat{\delta}_1, \tilde{\delta}_2 - \hat{\delta}_2$. Finally, the bias adjusted estimates are $\widehat{\beta}_1 \equiv \hat{\beta}_1 - [\tilde{\beta}_1 - \hat{\beta}_1], \widehat{\beta}_2 \equiv \hat{\beta}_2 - [\tilde{\beta}_2 - \hat{\beta}_2], \widehat{\delta}_1 = \tilde{\delta}_1 - [\tilde{\delta}_1 - \hat{\delta}_1]$, $\widehat{\delta}_2 = \tilde{\delta}_2 - [\tilde{\delta}_2 - \hat{\delta}_2]$.

We use $s_t - s_{t-1} = e_{1,t}$ and $GZ_t = \alpha + \widehat{\beta}_1 GZ_{t-1} + \widehat{\beta}_2 GZ_{t-2} + \widehat{\delta}_1 s_{t-1} + \widehat{\delta}_2 s_{t-2} + e_{2,t}$ to generate the artificial data for the regression of interest: $s_{t+h} - s_t = \alpha + \beta_1 GZ_t + e_t$