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Forecasting the U.S. Dollar in the 21st Century

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ABSTRACT

A long-standing puzzle is the near-random-walk behavior of exchange rates. Recent literature has proposed models to forecast exchange rates at medium- and long-horizons. Such tests suffer from small-sample bias but inferring the true test distribution is difficult. We propose two approaches to address the problem. First, since economists are interested in the value of economic models versus purely statistical models, we propose a horse-race that pits the economic models not against the random walk, but against the forecasts from the level of the exchange rate. These economic models are challenged because the level of the exchange rate appears to be a more powerful predictor than "global risk" variables. We also propose a second more general but less powerful test. But with both tests we demonstrate using bootstraps that the random walk cannot be rejected, so the predictive power of the lagged exchange rate and many other variables is illusory.

1. Introduction

The "gold standard" for testing exchange rate models is evidence they can produce lower mean-squared forecast errors of changes in the exchange rate 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. This forecasting failure has been considered a significant shortcoming of the conventional models – an indication of "exchange rate disconnect." Meese and Rogoff (1983) first demonstrated that the exchange-rate models of the 1970s were not helpful for forecasting. Mark (1995) attempted to rescue the standard approach by showing that there might be long-run forecasting power from simple traditional models. Engel and West (2005) prove that under some conditions, the inability to forecast future changes in exchange rates might be an inherent feature of many monetary models. Rossi (2013) surveys well over one hundred papers on the topic but concludes "the predictive ability of the fundamentals is time-varying and occasional." This conclusion agrees with the studies of Cheung et al. (2005, 2019), who find "model/specification/currency combinations that work well in one period and one performance metric will not necessarily work well in another period and alternative performance metric." Itskhoki and Mukhin (2021) list the random-walk behavior of the exchange rate as the first in their list of major puzzles that "conventional international macro models" cannot account for.

This puzzle has been a stumbling block for macroeconomic models of exchange rates, because, as Rogoff (2007) puts it, "Ultimately, there is no question that the aim is to have models that can forecast out of sample (as opposed to simply fit out of sample), as well as models that are useful for policy analysis." Moreover, Alvarez et al. (2007) argue that random-walk behavior of

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exchange rates is incompatible with economic models that imply monetary policy has no effect on ex ante excess returns (that is, models in which uncovered interest parity holds.) Also, from the perspective of predicting excess returns, given that nominal exchange rate changes are much more volatile than nominal interest rate differentials, an inability to reject a random walk in exchange rates generally coincides with low power in forecasting excess returns. For example, as Engel (1996, 2014) notes, while the well-known Fama (1984) test for uncovered interest parity finds evidence that the interest rate differential has statistically significant forecasting power for excess returns, the R-squared of those regressions tends to be very low.

In recent years, new studies have found evidence of predictability, particularly at medium-run horizons of 1- to 5- years, especially using measures of global financial and economic uncertainty to help forecast the dollar in data over the past two decades. These studies rely on the well-established notion that economic models might be able to predict at longer horizons even when their short-run forecasting is weak if the "true" model involves a complex lag structure or non-linearities which are difficult to specify precisely. (See in particular Kilian and Taylor (2003), Marcellino et al. (2006) and Pincheira and West (2016). The survey of exchange rate forecasting by Rossi (2013) considers the "direct method" of forecasting at longer horizons.)

A drawback of long-horizon forecasts is small-sample bias. When time series are persistent, a sample as small as the 22 years since the advent of the euro may be "small", in that test statistics might be subject to considerable biases that are not easily corrected with standard statistics. As the literature has shown, it is not so easy to assess this small sample bias using simulation methods when the forecasts are based on some variable or variables, x_t. How should x_t be modeled when the null is that the change in the log of the exchange rate, $s_{t+j} - s_t$, 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.

Also, there is the question of whether x_t is stationary. For example, we find that the detrended log of Overnight Repo outstanding of the primary dealers might have considerable forecasting power for changes in the exchange rate. But if this variable has a unit root, then 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.

We propose two solutions to this problem of assessing the small-sample bias. The first makes use of the fact that researchers are not interested in forecasting the exchange rate per se, but rather whether economic or financial models are useful in making forecasts. We propose to examine whether a set of economic variables – in particular, measures of "global risk" which recent literature has focused on – add forecasting power to the lagged level of the log of the exchange rate itself. In other words, we suggest replacing the random walk norm with the standard of "can the model out-forecast the lagged exchange rate?" Even if macroeconomic models do forecast better than the random walk, they still would not meet the Rogoff (2007) criterion of being useful for making predictions if they produce worse forecasts than the simple projection based on the level of the exchange rate.

The standard in the literature has been, in essence, to estimate the h-horizon equation:

$$s_{t+h} - s_t = \alpha_h + \beta_h^X x_t + u_{t+h} \tag{1}$$

Evidence of "in-sample" predictive power of the economic model is whether the parameter β_h^X is significantly different than zero. Out-of-sample forecasting ability estimates (1) over rolling samples to create forecasts that can be compared to the forecasts of some standard, usually the random walk. But we suggest estimating:

$$s_{t+h} - s_t = \alpha_h + \beta_h^{XX} x_t + \beta_h^{SS} s_t + u_{t+h} \tag{2}$$

If β_h^{XX} is not different than zero in this regression (for the in-sample forecasting test), or if the inclusion of x_t does not improve the forecasting power out of sample for this model, researchers still face the problem that the economic variables do not contribute to the predictive power of a simple time-series specification.

In fact, using exchange rates of G10 currencies relative to the U.S. dollar (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)), we generally find in our empirical applications that x_t is not statistically significant in estimates of (2), even when it is in (1). Also, we find that setting $\beta_h^{XX} = 0$ in (2) produces better forecasts both in- and out-of-sample than specification (1). That is, a univariate forecast based on the level of the exchange rate appears to be better than forecasts based on the global financial variables. Additionally, inclusion of x_t in Eq. (2) does not significantly improve out-of-sample predictive power relative to the specification in which $\beta_h^{XX} = 0$.

But we go farther. It appears that univariate forecasts of $s_{t+k} - s_t$ based on s_t alone are significantly better than the random walk forecast of no change using statistical methods typically employed in the literature. 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. 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 0.76 for simple average of G9 currencies, >0.7 for six of the ten exchange rates, and >0.6 for all but one of the currencies. Moreover, we find that tests of out-of-sample forecasting power of the level of the exchange rate based on rolling regressions produce large Clark and West (2006) statistics that, under the asymptotic distribution (and corrected for serial correlation), are very highly significant for medium-horizon forecasts. However, these tests are also subject to sizeable small-sample bias.

We use bootstrap and Monte Carlo methods to correct for the small-sample properties of the test statistics more accurately. 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. Simulation-based tests are simple to construct in this case because there is no auxiliary variable to model under the null hypothesis. (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.) The tests indicate we may not be able to reject the simple hypothesis that the exchange rates follow a random walk at standard significance levels. While the small-sample biases in the "long-horizon" regressions 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 simulation-based tests of out-of-sample forecasting power for the level of the exchange rate cannot reject the null of a random walk.

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 and, 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. These findings pose a challenge for exchange rate forecasts based on economic models. It stands to reason that these models, which use economic and financial variables to forecast exchange rates, may also be subject to small-sample biases that are not easily corrected for with standard statistics.

Our second method proposes a simple universal procedure to simulate the global risk measures. Here, we find very limited evidence for rejecting the null of a random walk. This leads us to conclude that the small-sample properties of forecasts based on economic variables must be carefully investigated.

This second test might not be powerful relative to particular specifications of the behavior of the auxiliary macro/financial variables under the null hypothesis. In fact, we emphasize at this point that our purpose here is not to criticize any specific study that has demonstrated empirical support for an exchange rate model. We have not tried to reproduce the exact specification of any model from the literature, so further study may find that some models hold up against concerns about small-sample bias. We instead intend simply to suggest that extra care be given in assessing the goodness of fit of in-sample medium-run forecasts and the out-of-sample forecasting power of models over medium horizons. (Some recent papers are Adrian and Xie (2020), Ca'Zorzi and Rubaszek (2020), Darvas and Schepp (2020), Eichenbaum et al. (2021), Evans (2020), Jiang et al. (2021), Kremens and Martin (2019), Lilley et al. (2019), Lustig et al. (2016), Liu and Shaliastovich (2022) and Ma and Zhang (2020).)

We suggest exploring whether economic and financial variables improve upon the forecasts of the current log-level exchange rate even when the forecasting power of the exchange rate by itself does not stand up to corrections for small-sample bias. If the level of the exchange rate itself produces forecasts of the medium-run change in the exchange rate that have lower mean-squared error than the economic and financial variables, but in turn is subject to small-sample bias, then small-sample bias must be a concern for the economic models. Moreover, in different, or longer samples, perhaps there will emerge evidence of the long-horizon forecasting power of the level of the exchange rate (and, in fact, in many cases in our study, while the random walk is not rejected, it nearly is at standard confidence levels.) But whether or not that happens, the Rogoff (2007) forecasting criterion for assessing economic models of the exchange rate surely would require that the model out-forecast the level (of the log) of the exchange rate.

In section 2, we examine the forecasting power of various economic and financial measures relative to the level of the exchange rate itself. In section 3, we re-examine the univariate exchange rate model using simulation methods. In section 4, we discuss a simple universal procedure (the second approach) to address the concern. We offer some conclusions and suggestions in the final section.

2. Dollar exchange rate forecasts

2.1. Data description

The log of nominal exchange rate, denoted as s_t, is the U.S. dollar price of a foreign currency. For all empirical exercises, we use exchange rates sample from January 1999 to March 2020. These are plotted in Fig. 1. The real exchange rate is defined as $q_t = s_t + p_t^* - p_t$ where p_t^*, p_t are foreign and home consumer price index. (We use CPI measured real exchange rates, but 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 for those countries.) The online data appendix reports the data sources and sample period for other relevant macro variables used.

We consider the predictive power of real exchange rates, since 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. However, many of these are based on data prior to 2000. See, for example, Mark (1995), Mark and Choi (1997), Engel et al. (2008), Jordá and Taylor (2012), Ca'Zorzi and Rubaszek (2020) and Eichenbaum et al. (2021). The global risk/macro variables that we consider 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

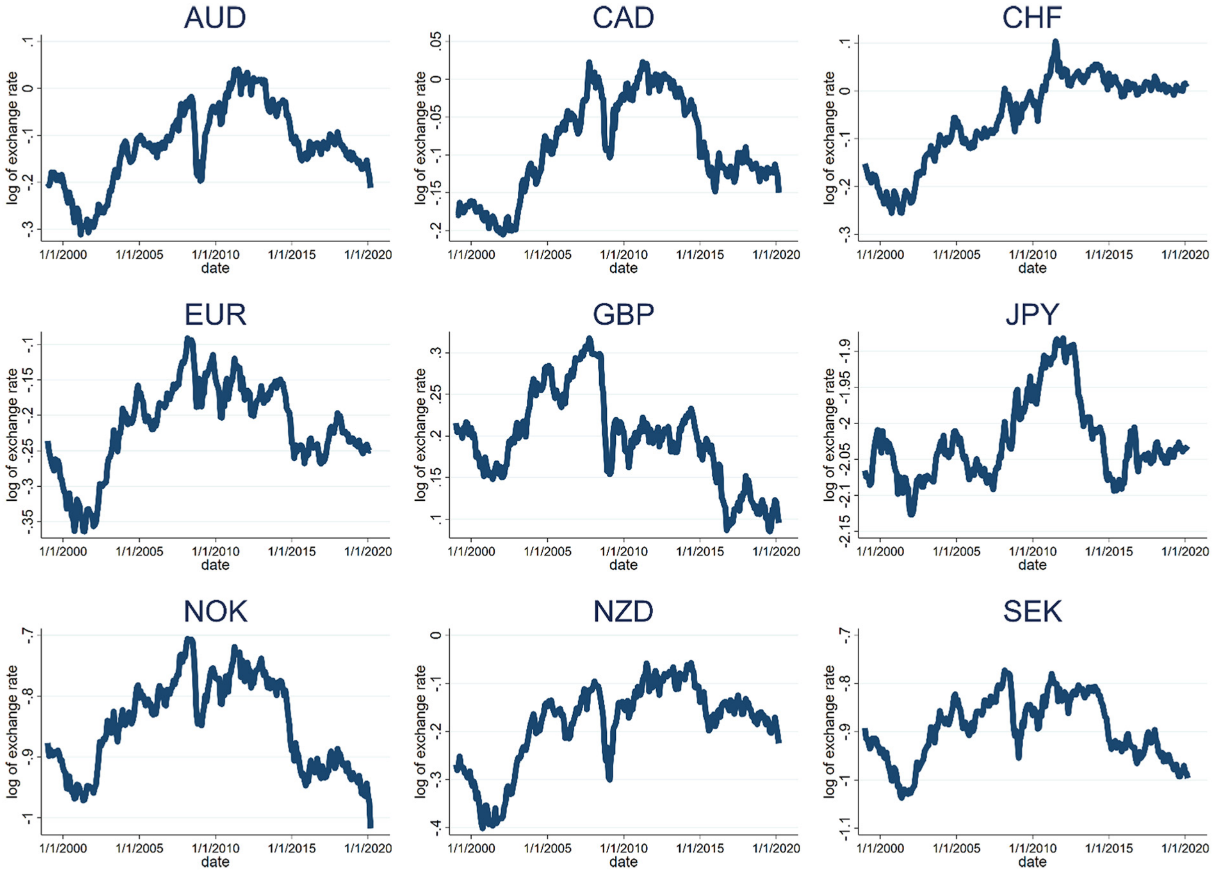

Fig. 1. U.S. Dollar Exchange Rates 1999 M1-2020 M3 (log of U.S. dollar per unit of foreign currency).

"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 dividend price ratio of S&P500; 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) "Log Repo" is the linearly detrended log of Overnight Repo outstanding of the primary dealers; 12) "Log Commercial Paper" is the linearly detrended log of Financial Commercial Paper outstanding of the primary dealers.

The US Treasury Premium is used in Du et al. (2018), Engel and Wu (2023) and Jiang et al. (2021). MAR global factor and GZ spread are used in Lilley and Rinaldi (2020). Price dividend ratio is used as a a proxy of SDF in the long-run risk literature. 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-Ozcan 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 (2021) and is the core friction is Gabaix and Maggiori (2015). Intermediary weighted return is used in Lilley and Rinaldi (2020). Repo and commercial paper are used in Adrian et al. (2018).

The data appendix provides the data source, the sample period, and the summary statistics of these macro variables, all of which are publicly available. (We detrend outstanding repo and financial commercial paper using the whole sample for in-sample forecasting, and for out-of-sample forecasting, we detrend using the 60 observations within the window.) Due to space limitations, we report only the results that forecast the simple average of exchange rate and provide a summary of the currency-by-currency regressions in online Appendix 2.

2.2. A new benchmark for exchange rate forecasting

Rossi (2013) highlights that "The toughest benchmark is the random walk without drift" (p.1063). In this subsection, we evaluate the forecasting performance of many macro variables that are proposed in the recent literature, and we show the superior performance of the level of exchange rate relative to all these variables.

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:

$$s_{t+h} - s_t = \alpha_h + \beta_h^{XX} X_t + \beta_h^{SS} s_t + u_{t+h} \tag{3}$$

$$s_{t+h} - s_t = \alpha_h + \beta_h^{S} s_t + u_{t+h} \tag{4}$$

$$s_{t+h} - s_t = \alpha_h + \beta_h^{X} X_t + u_{t+h} \tag{5}$$

$$s_{t+h} - s_t = u_{t+h} \tag{6}$$

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

2.3. Within-sample forecasts

Table 1 summarizes the regression results for the simple average of the dollar exchange rate of the G10 currencies. It presents the OLS estimates of the slope parameters with Newey-West standard errors, and the $R^2$of the regressions. (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.) Test statistics for the null of slope parameters equal to zero 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.

The first two columns of statistics in Table 1 directly compare the univariate in-sample forecasting power of the nominal exchange rate (first row in each horizon panel) to the economic variables (model (4) and model (5).) 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.

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 (3)). 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 Repo outstanding for primary dealers and the 10-year to 2-year U.S. term spread are significant at the 5% level and intermediary leverage at the 10% level. The inference on significance is based on the t-distribution for the economic variables, and on the Phillips-Perron statistic for the exchange rate.

At the medium horizons of 12-, 36- and 60-months, the exchange rate is always statistically significant at the 1% 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 rate is a strong predictor of exchange rate changes at all the horizons, in that it is statistically significant at the 1% level. Other variables show forecasting power at some horizons but not others. For example, the dividend price ratio is significant at the 12-month and 60-month horizons, but not at the 36-month, and the GZ spread at the 12- and 36-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 regressions is that in many cases, global risk variables that are not statistically significant in univariate forecasts become strongly significant when controlling for the level of the exchange rate. For example, at the 60-month horizon, three variables are significant at the 1% 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 do not add to the predictive power of the exchange rate 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.

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 some variables that appear to be the best at

Table 1
Regression statistics of in sample forecasting using simple average of exchange rate: Univariate model $s_{t+h} - s_t = \alpha + \beta^X X_t + e_{t+h}$, $s_{t+h} - s_t = \alpha + \beta^s s_t + e_{t+h}$ and multivariate model $s_{t+h} - s_t = \alpha + \beta^{XX} X_t + \beta^{ss} s_t + e_{t+h}$.

		Univariate model		Multivariate model		
		β^X	Adjusted R^2	β^{XX}	β^{ss}	Adjusted R^2
	Independent variables	(1)	(2)	(3)	(4)	(5)
1-month horizon forecast	s_t (nominal exchange rate)	−0.014	0.002			
($h = 1$)	q_t (real exchange rate)	−0.007	−0.003	0.019	−0.026	0.001
	US Treasury premium	−0.539	0.008	−0.763	−0.024	0.021
	MAR global factor	−0.001	0.000	−0.000	−0.012	0.001
	GZ spread	0.000	−0.003	0.000	−0.013	−0.001
	Dividend price ratio	0.159	0.000	0.348	−0.025	0.012
	Log VIX	0.001	−0.002	0.001	−0.013	−0.001
	US Term spread (5y-FF)	0.001	0.003	0.001	−0.015	0.006
	US Term spread (10y-2y)	0.001	0.004	0.002**	−0.022	0.015
	TED	−0.003	0.009	−0.003	−0.013	0.011
	Intermediary leverage	−0.008	−0.004	−0.081*	−0.038	0.015
	Interm. weighted return	−0.004	−0.004	−0.003	−0.015	−0.000
	Log Repo	0.002	0.001	0.006**	−0.038*	0.026
	Log Commercial Paper	−0.007	0.006	−0.006	−0.017	0.010
1-year horizon forecast	s_t (nominal exchange rate)	−0.219***	0.107			
($h = 12$)	q_t (real exchange rate)	−0.224***	0.067	0.053	−0.252***	0.109
	US Treasury premium	−0.388	−0.004	−2.823	−0.258***	0.137
	MAR global factor	−0.010	0.060	−0.006	−0.183***	0.127
	GZ spread	0.011**	0.086	0.010**	−0.193***	0.170
	Dividend price ratio	1.275	0.012	3.954***	−0.347***	0.227
	Log VIX	0.025	0.045	0.017	−0.196***	0.130
	US Term spread (5y-FF)	0.010	0.049	0.011	−0.226***	0.169
	US Term spread (10y-2y)	0.007	0.024	0.014	−0.292***	0.202
	TED	−0.015	0.018	−0.014	−0.218***	0.129
	Intermediary leverage	−0.020	−0.004	−0.98***	−0.505***	0.270
	Interm. weighted return	−0.027	−0.002	−0.023	−0.221***	0.112
	Log Repo	0.015	0.017	0.069***	−0.533***	0.396
	Log Commercial Paper	−0.067	0.055	−0.025	−0.337***	0.276
3-year horizon forecast	s_t (nominal exchange rate)	−0.689***	0.475			
($h = 36$)	q_t (real exchange rate)	−0.809***	0.319	0.240	−0.836***	0.479
	US Treasury premium	5.480	0.030	−1.167	−0.701***	0.474
	MAR global factor	−0.011	0.023	0.006	−0.720***	0.479
	GZ spread	0.027**	0.194	0.020***	−0.626***	0.573
	Dividend price ratio	−3.009	0.034	3.260	−0.797***	0.506
	Log VIX	0.069**	0.136	0.038	−0.634***	0.512
	US Term spread (5y-FF)	0.008	0.009	0.009	−0.693***	0.492
	US Term spread (10y-2y)	−0.005	0.000	0.013	−0.750***	0.502
	TED	0.018	0.010	0.018	−0.688***	0.487
	Intermediary leverage	0.937	0.130	−0.844	−0.933***	0.521
	Interm. weighted return	−0.099**	0.006	−0.087**	−0.687***	0.481
	Log Repo	−0.021	0.014	0.098***	−1.151***	0.775
	Log Commercial Paper	0.008	−0.005	0.121***	−0.911***	0.661
5-year horizon forecast	s_t (nominal exchange rate)	−1.111***	0.759			
($h = 60$)	q_t (real exchange rate)	−1.616***	0.631	0.168	−1.209***	0.758
	UST premium	10.590*	0.073	0.255	−1.108***	0.757
	MAR global factor	−0.011	0.011	0.016*	−1.186***	0.787
	GZ spread	0.022	0.071	0.007	−1.086***	0.766
	Dividend price ratio	−7.483	0.138	3.087***	−1.221***	0.774
	Log VIX	0.067	0.070	0.001	−1.110***	0.757
	US Term spread (5y-FF)	−0.014	0.020	−0.010	−1.104***	0.772
	US Term spread (10y-2y)	−0.038**	0.179	−0.014	−1.045***	0.780
	TED	0.037	0.031	0.035***	−1.109***	0.791
	Intermediary leverage	2.157***	0.431	−0.135	−1.152***	0.758
	Interm. weighted return	−0.010	−0.005	0.010	−1.111***	0.758
	Log Repo	−0.065	0.089	0.099***	−1.525***	0.888
	Log Commercial Paper	0.014	−0.005	0.167***	−1.305***	0.830

Notes: Exchange rate is simple average of all nine currencies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for one-sided test based on Phillips and Perron (1988) test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$). Newey-West standard errors with h-1 lags in parentheses.

forecasting exchange rates overall (e.g 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 asymptotic statistics that assume stationarity of the economic variables, is not valid.)

2.4. Out-of-sample forecasts

The previous sub-section examined the "in-sample" forecasting power of the level of the exchange rate and other macro variables. In recent years, the "gold standard" for evaluating the ability of a model to forecast is the out-of-sample forecasting criterion. We report these out-of-sample forecasting results in Table 2.

Specifically, the methodology that is widely adopted is to estimate forecasting equations (such as eqs. (3)–(5)) over subsamples of the data using rolling regressions (i.e., regressions with fixed sample sizes.) Here we use sub-sample sizes of five years (60 months). We estimate (3)–(5) 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, $\widehat{s_{t+h}-s_t}$, for $h = 1$, 12, 36, 60.

The literature has most often 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 uses the forecast of "no change" in the exchange rate to evaluate exchange rate models of the 1970s. (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 out-of-sample forecasts.) The random walk model, (6), with no drift, is nested in the model of Eq. (5) when $\alpha_h = 0$ and $\beta_h^S = 0$. 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. 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 first column of Table 2 tests whether the univariate forecasting model based on the global risk variable (model (5)) can produce forecasts with lower mean-squared error than the random walk model (model (6).) At the one-month horizon, there is weak evidence that any of the models can outperform a random walk prediction. At the 12-month horizon, some variables show strong predictability such as the real exchange rate. At the longer horizons of 36- and 60- months, all variables improve on the random walk forecast. This confirms the recent literature claim of predictability of exchange rates beyond medium horizon in out-of-sample sense.

Second, 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), which is appropriate because the forecasting models (models (4) and (5)) are not nested. These tests compare the forecasting ability of two non-nested model and conduct statistical inferences based on mean squared prediction errors.

These comparisons for the simple average exchange rate are presented in Table 2, in the second 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.

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 three 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 1% level in all cases at the 60-month horizon. (The only exception is the real exchange rate.)

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 third and fourth columns of Table 2 for the average exchange rate. In the third column we ask whether the multivariate model (the one in which both the exchange rate and one economic variable are used to generate forecasts, as in Eq. (3)) produces significantly lower RMSE than the univariate model which includes only the economic measure of global risk Eq. (5), using the Clark-West test 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 multivariate model are significantly better at the 10% level than the univariate model that uses only the measure of global risk, and at the 60-month horizon the confidence level is >99% in all cases.

The fourth column of Table 2 shows the Clark-West statistics for the test of whether the multivariate model Eq. (3) improves on the forecasts of the univariate model that uses the level of the exchange rate only Eq. (4). 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 conclusion based on the asymptotic out-of-sample tests is that at the longer horizons, the global risk variables by themselves improve forecasts based on the random walk. However, we find that forecasts based on the level of the exchange rate itself have lower out of sample RMSEs than ones based on the risk variables, and that adding the level of the exchange rate to a univariate forecasting model based on the risk variables does significantly improve out of sample predictive power at longer horizons. On the other hand, adding risk variables to the level of the exchange rate provides some but relatively limited predictability improvement.

Table 2

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

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

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

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

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

	Independent variables	Univariate X_t v.s. r.w.	Univariate s_t vs univariate X_t	Multivariate v.s. univariate X_t	Multivariate v.s. univariate s_t
		(i)	(ii)	(iii)	(iv)
1-month horizon forecast	s_t (nominal exchange rate)	−0.98			
($h = 1$)	q_t (real exchange rate)	−1.39	0.311	1.255	0.517
	US Treasury premium	−0.63	0.88	1.72**	0.22
	MAR global factor	−0.72	0.34	0.23	0.27
	GZ spread	0.51	0.47	−0.28	0.18
	Dividend price ratio	0.52	−0.10	−0.05	0.30
	Log VIX	0.16	0.22	0.03	−0.59
	US Term spread (5y-FF)	−1.61	0.38	0.80	−0.17
	US Term spread (10y-2y)	−1.12	−0.03	0.52	0.15
	TED	−0.58	0.56	−0.15	−0.39
	Intermediary leverage	0.10	0.43	−0.15	−0.28
	Interm. weighted return	−0.03	−0.04	0.41	−0.13
	Log Repo	0.12	0.84	0.24	−0.33
	Log Commercial Paper	0.90	0.56	−0.23	0.11
1-year horizon forecast	s_t (nominal exchange rate)	1.85**			
($h = 12$)	q_t (real exchange rate)	2.64***	−0.674	1.381*	1.520*
	US Treasury premium	1.90**	0.30	1.62*	1.47*
	MAR global factor	1.76**	0.28	1.54*	1.63*
	GZ spread	1.52*	0.86	1.64*	1.13
	Dividend price ratio	2.59***	1.04	1.86*	0.85
	Log VIX	1.25	0.71	1.86**	1.43
	US Term spread (5y-FF)	0.91	1.09	2.24**	1.82**
	US Term spread (10y-2y)	0.08	1.20	2.06**	2.01**
	TED	2.02**	0.74	1.74**	2.53***
	Intermediary leverage	1.80**	0.89	2.15**	1.62*
	Interm. weighted return	1.14	0.86	1.93**	−2.05
	Log Repo	2.20**	0.64	2.24**	1.97**
	Log Commercial Paper	2.61***	0.44	2.32**	1.54*
3-year horizon forecast	s_t (nominal exchange rate)	3.44***			
($h = 36$)	q_t (real exchange rate)	6.00***	2.058**	2.265**	1.908**
	US Treasury premium	3.61***	2.38**	2.49***	0.10
	MAR global factor	2.92***	0.86	1.77**	0.56
	GZ spread	3.41***	0.76	2.11**	1.63*
	Dividend price ratio	4.21***	1.72*	3.62***	0.59
	Log VIX	2.82***	0.63	2.92***	1.98**
	US Term spread (5y-FF)	4.20***	3.02***	3.99***	2.15**
	US Term spread (10y-2y)	3.45***	3.38***	4.28***	0.79
	TED	3.17***	4.72***	4.07***	1.46
	Intermediary leverage	3.03***	2.21**	6.02***	1.10
	Interm. weighted return	3.13***	3.51***	5.54***	1.51*
	Log Repo	3.11***	3.78***	5.30***	1.39*
	Log Commercial Paper	2.88***	4.21***	4.52***	0.78
5-year horizon forecast	s_t (nominal exchange rate)	2.96***			
($h = 60$)	q_t (real exchange rate)	5.27***	0.523	0.952	0.879
	US Treasury premium	3.61***	3.65***	3.99***	−0.02
	MAR global factor	1.78**	3.11***	2.82***	1.55
	GZ spread	2.01**	2.65***	3.15***	0.95
	Dividend price ratio	3.11***	4.06***	5.10***	2.87***
	Log VIX	1.90**	2.80***	3.41***	0.73
	US Term spread (5y-FF)	3.53***	4.10***	5.27***	2.30**
	US Term spread (10y-2y)	3.84***	3.65***	4.13***	1.46*
	TED	2.97***	3.59***	4.47***	2.82***
	Intermediary leverage	2.91***	4.07***	5.31***	2.80***
	Interm. weighted return	2.91***	3.57***	4.99***	−1.44
	Log Repo	3.46***	3.52***	5.94***	1.91**
	Log Commercial Paper	2.71***	3.39***	3.93***	2.57***

Notes: Exchange rate is simple average of all nine currencies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for two-sided test for column (ii) and one-sided test for the rest. In column (ii), 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 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.

3. Small-sample test statistics for nominal exchange rate using simulation methods

We have seen using state-of-the-art asymptotic statistical tests that economic and financial variables that proxy for global risk do not help to provide better forecasts than those based solely on the level of the exchange rate. In this section, we show using simulation methods that the apparent forecasting power of the level of the exchange rate may not be significant – that small-sample bias clouds the inference based on asymptotic statistics.

Before proceeding to the tests based on simulations, we briefly summarize some further details of the exchange-rate-based forecasts. In the previous section, we focused on forecasts of the simple average of the G10 exchange rates, but using the standard statistical inference, uncorrected for small-sample bias, the level of the exchange rate appears to have strong forecasting power for the individual currencies as well. We report those findings in first three columns of Table 3 and first and fourth columns of Table 4 and note the following highlights: (More detailed regression tables are reported in the online appendix tables 5 and 6.)

In Table 3, s_t is not a good predictor of one-month ahead changes in the exchange rate. β_1^S from Eq. (4) is insignificantly different from zero for all the currencies. The adjusted R^2 values are all <0.01 in third column of Table 3. We also estimate equation a version of Eq. (4) in a panel form with country (i) fixed effects, 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. (As the extended notes detail, we use the unit root tests for panels of Choi (2001) to draw statistical inference.)

At the 12-, 36-, and 60-month horizons, the level of the exchange rate is significant at the 1% level for all the currencies. We also estimate a fixed-effect panel and calculate standard errors using the Driscoll and Kraay method, and again find the slope is statistically significant.

The apparent forecasting power for the 36-month and 60-month changes in the exchange rate is striking. 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 dollar/euro rate, 0.76 for the simple average (SA) exchange rate, and 0.66 for the within R^2 in the panel regression.

In the first and fourth columns of Table 4, the Clark-West statistics for tests of the out-of-sample forecasting power of the level of the exchange rate are equally striking. While at the one-month forecasting horizon, the forecasting equation does not produce significantly better forecasts than the random walk, at the 12-month, 36-month, and 60-month forecasts, the model's predictions are significantly better for all currencies as well as 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 5% level for all exchange rates and at the 1% level for most; and, at the 60-month horizon the significance level is 1% for all but two currencies.

3.1. 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. (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), Boudoukh et al. (2008, 2022) and many others.) As we demonstrate in this section, the very large t-statistics, very large Clark West statistics and very high R^2 values described above are nonetheless not statistically significant at standard significance levels, once we have accounted for small-sample biases.

We present the simulation results of nominal exchange rates in Tables 3 (column (4)–(10)) and Table 4 (column (2), (3), (5), (6)).

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. Our methods of simulations are standard and described in detail in the online 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 for the Monte Carlo and bootstrap exercises in order to construct the distributions of the statistics we report in Tables 4–6.

3.2. Within-sample forecasts

Table 3 reports the results based on the simulated distribution. To show that our simulation results hold largely for every single G-10 currency, we report the regression for each of the currency exchange rate relative to the US, the simple average and also in panel format. 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 (column (1), (4), (7)) from actual data of regression (4). It then presents the p-values for one-sided tests (negative slope coefficient, positive R^2) based on the Monte Carlo and bootstrap simulated distribution, meaning the critical value at which the null hypothesis of a random walk would be rejected.

Table 3
Regression statistics of in-sample forecasting using simulated data: $s_{t+h} - s_t = \alpha + \beta s_t + e_{t+h}$.

	Actual data			Beta		NW t-stat		Adjusted R^2	
	Beta	NW t-stat	Adjusted R^2	MC p-value	BS p-value	MC p-value	BS p-value	MC p-value	BS p-value
Currency	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)	(10)
1-month horizon forecast ($h = 1$)									
AUD	−0.016	−1.41	0.004	0.52	0.52	0.57	0.58	0.57	0.57
CAD	−0.017	−1.69	0.006	0.50	0.50	0.44	0.44	0.50	0.51
CHF	−0.011	−1.19	0.002	0.67	0.69	0.66	0.68	0.65	0.67
EUR	−0.019	−1.41	0.005	0.45	0.45	0.57	0.57	0.52	0.52
GBP	−0.013	−1.11	0.000	0.63	0.62	0.71	0.71	0.74	0.73
JPY	−0.023	−1.73	0.008	0.35	0.36	0.42	0.42	0.41	0.41
NOK	−0.008	−0.66	−0.002	0.79	0.77	0.86	0.84	0.86	0.85
NZD	−0.020	−1.64	0.007	0.43	0.44	0.46	0.47	0.45	0.46
SEK	−0.018	−1.48	0.003	0.48	0.49	0.54	0.56	0.62	0.63
SA	−0.014	−1.28	0.003	0.60	0.80	0.64	0.63	0.64	0.74
Panel	−0.015	−1.91	0.003	0.47	0.48	0.65	0.64	0.84	0.84
1-year horizon forecast ($h = 12$)									
AUD	−0.224***	−2.03	0.113	0.45	0.44	0.57	0.56	0.49	0.49
CAD	−0.191***	−2.11	0.111	0.53	0.52	0.54	0.53	0.50	0.50
CHF	−0.123***	−1.66	0.084	0.70	0.71	0.67	0.68	0.60	0.60
EUR	−0.257***	−2.18	0.131	0.37	0.36	0.50	0.51	0.42	0.41
GBP	−0.216***	−1.40	0.075	0.46	0.46	0.74	0.75	0.64	0.64
JPY	−0.283***	−2.02	0.143	0.31	0.32	0.57	0.57	0.38	0.37
NOK	−0.193***	−1.73	0.073	0.52	0.52	0.66	0.66	0.65	0.65
NZD	−0.252***	−1.95	0.139	0.39	0.40	0.60	0.60	0.40	0.41
SEK	−0.301***	−2.14	0.127	0.29	0.29	0.53	0.54	0.44	0.45
SA	−0.219***	−1.92	0.111	0.45	0.46	0.60	0.63	0.49	0.46
Panel	−0.217***	−2.39	0.110	0.30	0.30	0.70	0.69	0.37	0.37
3-year horizon forecast ($h = 36$)									
AUD	−0.672***	−4.75	0.45	0.39	0.39	0.26	0.26	0.29	0.28
CAD	−0.622***	−3.06	0.40	0.45	0.44	0.52	0.50	0.37	0.37
CHF	−0.404***	−5.09	0.48	0.66	0.67	0.21	0.22	0.24	0.24
EUR	−0.733***	−5.13	0.52	0.33	0.34	0.22	0.21	0.19	0.18
GBP	−0.618***	−2.08	0.22	0.45	0.46	0.70	0.71	0.66	0.66
JPY	−0.946***	−4.78	0.49	0.16	0.15	0.25	0.24	0.22	0.22
NOK	−0.652***	−2.72	0.33	0.42	0.42	0.58	0.58	0.49	0.49
NZD	−0.712***	−5.90	0.57	0.35	0.37	0.15	0.16	0.12	0.13
SEK	−0.764***	−3.71	0.42	0.32	0.31	0.41	0.40	0.35	0.35
SA	−0.689***	−4.07	0.48	0.37	0.37	0.34	0.34	0.25	0.21
Panel	−0.657***	−5.26	0.42	0.20	0.21	0.31	0.31	0.11	0.11
5-year horizon forecast ($h = 60$)									
AUD	−1.030***	−7.48	0.73	0.35	0.36	0.20	0.19	0.12	0.12
CAD	−1.125***	−6.31	0.73	0.28	0.26	0.28	0.27	0.12	0.11
CHF	−0.606***	−6.10	0.71	0.66	0.67	0.28	0.29	0.14	0.15
EUR	−1.122***	−10.72	0.78	0.27	0.28	0.08	0.08	0.07	0.07
GBP	−1.25***	−3.65	0.44	0.17	0.17	0.58	0.58	0.56	0.55
JPY	−1.283***	−4.89	0.68	0.15	0.14	0.43	0.42	0.19	0.19
NOK	−1.262***	−5.81	0.60	0.16	0.16	0.31	0.31	0.31	0.32
NZD	−0.964***	−13.13	0.82	0.40	0.41	0.04	0.05	0.04	0.04
SEK	−1.244***	−7.16	0.69	0.18	0.18	0.22	0.22	0.17	0.18
SA	−1.111***	−7.33	0.76	0.29	0.28	0.20	0.20	0.09	0.06
Panel	−1.030***	−10.67	0.66	0.14	0.14	0.11	0.11	0.05	0.05

Notes: SA is the regression with simple average of all nine currencies. For the actual data, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for one-sided test based on Phillips and Perron (1988) test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$). MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Newey-West standard errors with h-1 lags are reported. 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. F-stat is reported for the panel regression.

Table 3 shows that in the simulated distributions, there is no 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 >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 based on asymptotic statistics, 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 <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

Table 4

5-year rolling window out-of-sample prediction error with simulated data: Univariate model $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}_{t-61,t} s_t$ vs random walk model ($\widehat{s_{t+h}-s_t} = 0$).

Currency		CW statistics: Actual data (1)	MC p-value (2)	BS p-value (3)		CW statistics: Actual data (4)	MC p-value (5)	BS p-value (6)
AUD	1-month horizon forecast ($h = 1$)	−1.07	0.84	0.83	3-year horizon forecast ($h = 36$)	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		0.04	0.43	0.43		3.83***	0.23	0.25
GBP		−1.50	0.92	0.91		2.19**	0.85	0.85
JPY		−0.90	0.78	0.79		2.36***	0.79	0.79
NOK		−1.36	0.90	0.90		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-year horizon forecast ($h = 12$)	1.29*	0.94	0.93	5-year horizon forecast ($h = 60$)	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		3.98***	0.05	0.05		7.98***	0.03	0.03
GBP		2.28**	0.60	0.59		4.10***	0.25	0.26
JPY		1.84**	0.80	0.80		3.92***	0.29	0.28
NOK		2.50***	0.48	0.47		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***	0.52	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. For the actual data, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for one-sided test based on Phillips and Perron (1988) test statistics compared with Dickey Fuller distribution without drift (population value of $\alpha = 0$). MC and BS stand for Monte Carlo and Bootstrap (with replacement) respectively. Each exercise simulates the data 5000 times. Newey-West standard errors with h-1 lags are reported. 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.

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 0.15 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 >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 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, 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.

3.3. Out-of-sample forecasts

Table 4 reports the p-values of out-of-sample forecasting, using the simulated distribution. We report the Clark West statistics for comparing the model with the nominal exchange rate as a predictor and the random walk, and the corresponding p-values generated by the Monte Carlo and bootstrap simulation.

The p-values from the simulated distribution in Table 4 do not show evidence of exchange-rate forecastability. Here, again, we see that there is noteworthy small-sample bias. 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 these values are >0.30, except for the Canadian dollar at the 12- and 36-month horizon (0.24 and 0.30, 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.

Table 5
Regression statistics of in sample forecasting using simulated data: $s_{t+h} - s_t = \alpha + \beta X_t + e_{t+h}$.

		Beta		t-stats		Adjusted R^2	
		Actual data	MC p-value	Actual data	MC p-value	Actual data	MC p-value
	Currency	(1)	(2)	(3)	(4)	(5)	(6)
1-month horizon forecast ($h = 1$)	q_t (real exchange rate)	−0.007	0.50	−0.60	0.60	0.00	0.57
	US treasury premium	−0.539	0.34	−1.05	0.20	0.008	0.11
	MAR global factor	−0.001	0.35	−1.02	0.86	0.000	0.46
	GZ spread	0.0003	0.76	0.40	0.96	−0.003	0.63
	Dividend price ratio	0.159	0.13	0.73	0.08	0.00	0.74
	Log VIX	0.001	0.86	0.54	0.92	−0.002	0.52
	US Term spread (5y-FF)	0.001	0.18	1.31	0.27	0.003	0.20
	US Term spread (10y-2y)	0.001	0.10	1.49	0.11	0.004	0.17
	TED	−0.003	0.45	−0.98	0.47	0.009	0.11
	Intermediary leverage	−0.008	0.36	−0.26	0.34	−0.004	1.00
	Interm. weighted return	−0.004	0.71	−0.25	0.84	−0.004	1.00
	Log Repo	0.002	0.38	0.98	0.63	0.001	0.87
	Log Commercial Paper	−0.007	0.25	−1.41	0.40	0.006	0.16
1-year horizon forecast ($h = 12$)	q_t (real exchange rate)	−0.224	0.26	−1.82	0.94	0.07	0.51
	US treasury premium	−0.388	0.57	−0.10	0.61	−0.004	0.92
	MAR global factor	−0.010	0.42	−1.24	0.97	0.060	0.38
	GZ spread	0.011	0.12	2.54	0.16	0.086	0.14
	Dividend price ratio	1.275	0.34	0.84	0.31	0.012	0.48
	Log VIX	0.025	0.25	1.44	0.56	0.045	0.25
	US Term spread (5y-FF)	0.010	0.20	1.31	0.45	0.049	0.27
	US Term spread (10y-2y)	0.007	0.28	0.97	0.39	0.024	0.45
	TED	−0.015	0.42	−0.74	0.69	0.018	0.36
	Intermediary leverage	−0.020	0.49	−0.07	0.49	−0.004	0.97
	Interm. weighted return	−0.027	0.56	−0.68	0.63	−0.002	0.54
	Log Repo	0.015	0.08	0.73	0.68	0.017	0.50
	Log Commercial Paper	−0.067	0.34	−1.28	0.74	0.055	0.29
3-year horizon forecast ($h = 36$)	q_t (real exchange rate)	−0.809	0.19	−2.49	0.93	0.32	0.42
	US treasury premium	5.480	0.70	1.16	0.81	0.030	0.49
	MAR global factor	−0.011	1.00	−1.15	1.00	0.023	0.75
	GZ spread	0.027	0.10	2.59	0.30	0.194	0.13
	Dividend price ratio	−3.009	0.82	−0.61	0.98	0.034	0.48
	Log VIX	0.069	0.12	2.16	0.44	0.136	0.16
	US Term spread (5y-FF)	0.008	0.77	0.86	0.76	0.009	0.72
	US Term spread (10y-2y)	−0.005	0.91	−0.44	0.93	0.000	0.85
	TED	0.018	0.54	0.79	0.55	0.010	0.67
	Intermediary leverage	0.937	0.71	1.32	0.85	0.130	0.36
	Interm. weighted return	−0.099	0.17	−2.44	0.11	0.006	0.22
	Log Repo	−0.021	0.26	−0.59	0.68	0.014	0.72
	Log Commercial Paper	0.008	0.44	0.09	0.46	−0.005	1.00
5-year horizon forecast ($h = 60$)	q_t (real exchange rate)	−1.62	0.01	−7.85	0.34	0.63	0.27
	US treasury premium	10.590	0.32	1.67	0.69	0.073	0.35
	MAR global factor	−0.011	1.00	−0.68	1.00	0.011	0.83
	GZ spread	0.022	0.44	1.49	0.84	0.071	0.46
	Dividend price ratio	−7.483	0.43	−1.32	0.71	0.138	0.24
	Log VIX	0.067	0.25	1.22	0.93	0.070	0.35
	US Term spread (5y-FF)	−0.014	0.37	−1.27	0.40	0.020	0.67
	US Term spread (10y-2y)	−0.038	0.15	−2.29	0.35	0.179	0.28
	TED	0.037	0.34	1.02	0.52	0.031	0.54
	Intermediary leverage	2.157	0.21	3.90	0.25	0.431	0.09
	Interm. weighted return	−0.010	1.00	−0.27	1.00	−0.005	0.94
	Log Repo	−0.065	0.13	−1.19	0.53	0.089	0.48
	Log Commercial Paper	0.014	0.42	0.10	0.47	−0.005	0.99

Notes: SA is the regression with simple average of all nine currencies. MC stands for Monte Carlo. Each exercise simulates the data 5000 times. Inferences are based on Newey-West standard errors with h-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. p-values of one-sided test are reported.

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 the sole rejection 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 weak 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.

Table 6

5-year rolling window out-of-sample prediction error with simulated data: Univariate model $\widehat{s_{t+h}-s_t} = \hat{\alpha} + \hat{\beta}_{t-61,t}X_t$ vs random walk model ($\widehat{s_{t+h}-s_t} = 0$).

Currency		CW statistics Actual data (1)	MC p-value (2)		Actual data (4)	MC p-value (5)
q_t (real exchange rate)	1-month horizon forecast	−1.39	0.90	3-year horizon forecast	6.00	0.01
US treasury premium	($h = 1$)	−0.63	0.68	($h = 36$)	3.61	0.05
MAR global factor		−0.72	0.72		2.92	0.20
GZ spread		0.51	0.26		3.41	0.07
Dividend price ratio		0.52	0.24		4.21	0.053
Log VIX		0.16	0.37		2.82	0.14
US Term spread (5y-FF)		−1.61	0.93		4.20	0.03
US Term spread (10y-2y)		−1.12	0.84		3.45	0.08
TED		−0.58	0.57		3.17	0.08
Intermediary leverage		0.10	0.39		3.03	0.13
Interm. weighted return		−0.03	0.45		3.13	0.06
Log Repo		0.12	0.42		3.11	0.20
Log Commercial Paper		0.90	0.14		2.88	0.15
q_t (real exchange rate)	1-year horizon forecast	2.01	0.61	5-year horizon forecast	5.27	0.07
US treasury premium	($h = 12$)	1.90	0.31	($h = 60$)	3.61	0.11
MAR global factor		1.76	0.52		1.78	0.76
GZ spread		1.52	0.55		2.01	0.56
Dividend price ratio		2.59	0.12		3.11	0.20
Log VIX		1.25	0.61		1.90	0.58
US Term spread (5y-FF)		0.91	0.82		3.53	0.14
US Term spread (10y-2y)		0.08	0.97		3.84	0.14
TED		2.02	0.23		2.97	0.21
Intermediary leverage		1.80	0.46		2.91	0.27
Interm. weighted return		1.14	0.45		2.91	0.15
Log Repo		2.20	0.38		3.46	0.26
Log Commercial Paper		2.61	0.13		2.71	0.30

Notes: SA is the regression with simple average of all nine currencies. MC stands for Monte Carlo. Each exercise simulates the data 5000 times. Inferences are based on Newey-West standard errors with h-1 lags. The simulated panel data are simulated with empirical variance-covariance matrix. p-values of one-sided test are reported.

4. A second approach to address the small sample bias

Ideally, small sample bias adjustment of the macro variables should be approached on a case-by-case basis for each forecasting model. The relationship of s_t and x_t under the null hypothesis will depend on the particular economic model that motivates the choice of macroeconomic or financial variable used to forecast exchange rates. However, individual assessment of each macro variables is beyond the scope of this paper. Instead, we propose a simple universal procedure of small-sample bias correction that we apply to all of the forecasts based on economic measures of global risk. In brief, our procedure is to estimate a vector autoregression for $y_t = (s_t, x_t)'$. We can write the VAR as:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots \Phi_k y_{t-k} + e_t \tag{7}$$

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 (In our application, we choose a lag length based on the AIC). We then attempt to correct for small sample bias in these VAR estimates using the bootstrap-after-bootstrap procedure of Kilian (1998). (See online Appendix 3 for the estimation details.)

Our simulation procedure 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 (7), using the estimated parameters for the x_t process and the estimated covariance matrix of e_t.

Table 5 and Table 6 report the in-sample and out-of-sample statistics of this exercise, using the simple average of the exchange rates.

Table 5 reports the estimated slope coefficient, t-statistic and adjusted R^2 of the in-sample forecasting Eq. (5) using the actual data and the p-value using the simulated distribution. None of these economic/financial predictors are significant using the simulated distribution, except for the real exchange rate slope coefficient at 5-year horizon. The t-statistics and adjusted R^2 are not significant at the 10% level for the real exchange rate. The in-sample predictability of the macro variables is exceedingly weak once we take into account the small sample bias.

Table 6 reports the out-of-sample statistics. We report the Clark-West statistics of the rolling forecasting regression using each macro variable vs. the random walk model and the corresponding p-value using the simulated distribution. We see that the significant out-of-sample predictive power of the macro variables largely disappears with the small bias adjustment using the simulation methods. None of the macro variables generate a lower mean square error than a random walk at 1-month, 12-month and 60-month horizons, with a minimum p-value of 0.07. The Clark-West statistics of the real exchange rate, US treasury premium and the term spread between 5-year US Treasury yield and overnight Fed Fund rate are significant at 5% level at 36-month horizon. We show that in the online appendix this is not a universally strong prediction. When we look at the prediction currency by currency rather than just using the simple average exchange rate, the predictability is further weakened and not significant.

So, using asymptotic inference, it appeared that the macro variables 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.

5. Conclusions

To reiterate, we find that the level of the exchange rate appears to have forecasting power that exceeds those from forecasts using measures of global risk. By itself, this poses a challenge, because it suggests that economic models still are not extremely useful for forecasting exchange rates, since forecasts based on simply the level of the exchange rate produce lower mean-squared errors.

But we have also seen that the forecasting power of the level of the exchange rate – and by extension, the global risk variables – may be a chimera. Our simulation-based statistics find that the forecasts based on the level of the exchange rate do not offer strong evidence against the random-walk model. We suggest then the macroeconomic variables' forecasting power is also suspect, since they generally produce larger mean-squared forecasting errors and usually do not improve upon the forecasting power of the level of the exchange rate. We also propose a simple universal method for constructing simulation-based tests for forecasts from models based on macro variables and find the small-sample statistics from those do not reject a random-walk exchange rate. While our analysis does not provide a comprehensive case-by-case examination of every study that claims forecasting power for a particular economic model, it does suggest that care must be taken in assessing the small-sample properties of these tests.

Recall that Engel and West (2005) have demonstrated that a large range of exchange rate models have the implication that changes in the nominal exchange rate are nearly unpredictable. The evidence that this set of macroeconomic models are not useful in forecasting changes in the exchange rate once we properly account for small-sample bias does not necessarily indicate that these models are poor descriptions of the economic forces driving exchange rates, but other methods are then necessary to assess these models.

Data availability

Forecasting the U.S. Dollar in the 21st Century (Original data) (Mendeley Data)

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2023.103715.

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