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Do stock markets have predictive content for exchange rate movements?

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Abstract

This paper examines short-horizon exchange rate predictability and investigates whether stock returns contain information for forecasting daily exchange rate movements. Inspired by the uncovered equity parity condition, we show that stock return differentials have in-sample and out-of-sample predictive power for nominal exchange rates with short horizons (1-day-ahead predictions). That is, stock markets inform us about exchange rate movements, at least in the case of high-frequency data.

KEYWORDS
exchange rates, forecasting, uncovered equity parity

1 | INTRODUCTION

Following the seminal paper by Meese and Rogoff (1983), beating the random walk model in forecasting nominal exchange rates out-of-sample has posed a challenge in the field of international economics. In their highly cited work, Meese and Rogoff show that exchange rate forecasting with macroeconomic fundamentals at short horizons has been frustratingly disappointing. Follow-up studies, including Cheung, Chinn, and Pascual (2005), show that no single exchange rate model can consistently out-forecast a random walk model in out-of-sample predictions, considering a variety of forecasting horizons.

Recently, more positive short-term forecasting results have been reported by a growing number of studies. For example, Gourinchas and Rey (2007) show that the exchange rate is forecastable in- and out-of-sample at one quarter and beyond using net foreign assets models. Molodtsova and Papell (2009) provide strong evidence of short-horizon exchange rate predictability with Taylor-rule fundamentals based on the out-of-sample test statistic developed by Clark and West (2007). Li, Tsiakas, and Wang (2015) find that economic fundamentals have predictive power for exchange rates when prediction is based on a kitchen-sink regression that incorporates a large number of economic fundamentals. See Rossi (2013) for a thorough review of the recent literature. According to Rossi:

> [a]lthough there is disagreement in the literature, overall the empirical evidence is not favorable to traditional economic predictors (such as interest rates, prices, output, and money). Instead, Taylor-rule fundamentals and net foreign asset positions have promising out-of-sample forecasting ability for exchange rates. The consensus in the literature is that the latter fundamentals have more out-of-sample predictive content than traditional fundamentals. (Rossi, 2013, p. 1066)

However, Rogoff and Stavrakeva (2008) have shown that the successful forecasting of short-term exchange rate movements may come from "misinterpretation of some newer out-of-sample test statistics for nested models, over-reliance on asymptotic out-of-sample test statistics and failure to check for robustness to the time period sampled." In particular, they argue that the test suggested by Clark and West (2007) is more likely to test whether the exchange rate follows a random walk rather than whether the proposed model outperforms the random walk model. That is, the out-of-sample forecasting performance is overpraised based on misinterpretation of some out-of-sample tests for nested models.

The novelty of this paper is to propose a new leading indicator to forecast exchange rate movements, namely, the stock return differential between domestic stocks and US stocks. This predictor is motivated by the close link between the stock and foreign exchange markets in an emerging theory, known as uncovered equity parity (UEP), as documented by Cappiello and De Santis (2005, 2007), Hau and Rey (2006), Kim (2011), and Curcuru, Thomas, Warnock, and Wongswan (2014). Consider a domestic investor with money invested in both domestic and foreign equity markets. According to Hau and Rey, when the foreign equity market outperforms the domestic market, domestic investors are exposed to higher exchange rate risks. They will repatriate some of their foreign equities to reduce their exchange rate risk. Then, the associated selling of foreign currency leads to depreciation of the foreign currency. The UEP theory suggests that a strong equity market is associated with a weak currency because of portfolio rebalancing.

The statistical validity of the UEP condition has been verified in Cappiello and De Santis (2007), Hau and Rey (2006), and Gelman, Jochem, Reitz, and Taylor (2015). By contrast, Curcuru et al. (2014) conduct a thorough examination of the portfolio rebalancing behavior of US investors, and find that, consistent with UEP, investors sell foreign equities that have recently performed well. However, the currency exposure-reduction actions proposed in the UEP literature do not appear to be supported by the evidence: Data show that the motivation is not to reduce foreign currency risk, but to correctly time markets that subsequently perform relatively well. Moreover, Cenedese, Payne, Sarno, and Valente (2016) employ a cross-sectional portfolio-based test, and find that the explanatory power of stock returns for exchange rate movements is limited using monthly data.

The positive correlation between stock return differentials and exchange rate movements implied by the UEP condition contradict the “conventional wisdom” that a strong equity market comes with a strong currency. However, the existing literature also suggests that the correlation may be consistent with the conventional wisdom, and take the opposite sign. For example, the correlation could be negative because of a risk premium (see Cenedese et al., 2016) or the behavior of trend chasing and momentum investing (see, e.g., Bohn & Tesar, 1996; Griffin, Nardari, & Stulz, 2004). Hence there seems to be no consensus with regard to the sign of the correlation between stock return differentials and exchange rate movements in theory. Nevertheless, as exchange rate movements have been somewhat difficult to predict, UEP may provide a fresh way of thinking about exchange rate predictability using information from stock markets. Moreover, studies in the traditional exchange rate forecasting literature tend to use macroeconomic fundamental as the predictor (see, e.g., Engel, Mark, & West, 2007; Mark, 1995; Mark & Sul, 2001; Molodtsova & Papell, 2009), but the fundamentals-based exchange rate model is not feasible for a real-time forecasting experiment. There is a time lag between the reference period and the announcement release time, and macroeconomic data such as price level, real output, and money supply are revised over time. As stock prices are not subject to revision, their usefulness in real-time data forecasts give them an advantage over other potential predictors. In this paper, we use daily data to examine the forecasting ability of the UEP model because portfolio rebalancing behavior is commonly used in high-frequency trading to hedge an investment position. The predictive power of the stock return differential would be insignificant if lower frequency data are used (namely, monthly or quarterly) under the mechanism that the UEP suggests. It is worth noting that, in terms of forecasting horizon, our empirical exercise is close to the order flows literature that studies how actual transactions can affect exchange rates (see, e.g., Dunne, Hau, & Moore, 2010; Filipe, 2012). However, the advantage of using the stock return differential as a leading indicator is that timely stock price data are readily available for forecasting purposes, while order flows are required to be derived from the correlated belief changes by heterogeneous investor groups.

We consider the seven most-traded currencies, according to the Triennial Central Bank Survey of foreign exchange turnover in April 2016 by the Bank for International Settlements: the US dollar (USD), euro (EUR), Japanese yen (JPY), British pound (GBP), Australian dollar (AUD), Swiss franc (CHF), and Canadian dollar (CAD). The USD is used as a numeraire. We aim to investigate whether the stock return differential has in-sample and out-of-sample predictive power over nominal exchange rate movements. The in-sample tests are based on the significance of the coefficient (t-test) from a 1-day-ahead predictive regression model. The mean squared prediction error (MSPE) is used to evaluate the out-of-sample forecast performance. It is worth noting that we have conducted our forecasting exercise to address, in particular, the concerns raised by Rogoff and Stavrakeva (2008). Rather than relying on asymptotic inferences based on out-of-sample statistics, we implement the tests using a bootstrap method. Moreover, we focus on a forecasting performance evaluation with an MSPE that is smaller than the MSPE of the driftless random walk.

Finally, as different forecast windows may exhibit very different forecast performance, and the observed good performance results may be from a particular forecast window chosen by the researchers, we consider a bootstrap reality check to address such a data-snooping problem (see, e.g., White, 2000).

We find that stock return differentials outperform the random walk model in five of the six currency pairs (EUR/USD, JPY/USD, GBP/USD, AUD/USD and CAD/USD).[1] Moreover, the results are robust with respect to alternative benchmark models (the autoregressive model), an alternative forecasting objective (the level of exchange rates), and alternative model specifications (with other covariates). We thus tease out a strong connection between exchange rate movements and return differentials in a short horizon.

The structure of the paper is organized as follows. Section 2 presents the theoretical motivation for the proposed predictor. Section 3 describes the empirical framework. Data descriptions are reported in Section 4, and Section 5 provides the empirical results. Sections 6 and 7 explore the robustness of the empirical findings, and the conclusions follow in Section 8.

2 | THEORETICAL MOTIVATION

In this section, we use an asset pricing model to illustrate the relationship between stock return differentials and exchange rate movements, suggested by the UEP condition. Consider a simple two-period representative-agent model. Let a_t and a_t^* denote the holdings of domestic and foreign stocks, respectively. The representative consumer's problem is to choose consumption and asset holdings $\{c_t, c_{t+1}, a_t, a_t^*\}$ to maximize lifetime expected utility, subject to budget constraints as follows:

$$\max\ u(c_t) + \beta E_t\left[u(c_{t+1})\right],$$

subject to

$$\begin{aligned} p_t c_t &= p_t y_t - q_t a_t - q_t^* S_t a_t^*, \\ p_{t+1} c_{t+1} &= p_{t+1} y_{t+1} + (q_{t+1} + d_{t+1}) a_t + (q_{t+1}^* + d_{t+1}^*) S_{t+1} a_t^*, \end{aligned}$$

where S_t is the nominal bilateral exchange rate (the domestic currency cost of foreign currency), q_t is the stock price, d_t denotes the dividend, and y_t is the endowment. Variables with an asterisk denote the foreign counterparts, and q_t^* and d_t^* are quoted in foreign currency.

[1]We use European quotations for all currency pairs for consistency.

The Euler equations for domestic investors are

$$\begin{aligned} 1 &= E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} \frac{p_t}{p_{t+1}} \frac{q_{t+1} + d_{t+1}}{q_t}\right], \\ 1 &= E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} \frac{p_t}{p_{t+1}} \frac{q_{t+1}^* + d_{t+1}^*}{q_t^*} \frac{S_{t+1}}{S_t}\right]. \end{aligned}$$

We can rewrite the equations as follows:

$$E_t\left(R_{t+1}^d m_{t+1}^d\right) = 1, \tag{1}$$

$$E_t\left(R_{t+1}^f \frac{S_{t+1}}{S_t} m_{t+1}^d\right) = 1, \tag{2}$$

where $R_{t+1}^d = \frac{q_{t+1}+d_{t+1}}{q_t}$ and $R_{t+1}^f = \frac{q_{t+1}^*+d_{t+1}^*}{q_t^*}$ are the gross returns on domestic and foreign stocks, respectively, and $m_{t+1}^d = \beta \frac{u'(c_{t+1})}{u'(c_t)} \frac{p_t}{p_{t+1}}$ is the stochastic discount factor of the domestic investor. Clearly, from the domestic investor's perspective, foreign investment returns are exposed to exchange rate risk: $R_{t+1}^f \frac{S_{t+1}}{S_t}$.

Suppose that the stochastic discount factor (pricing kernel) is uncorrelated with the returns of the domestic and foreign investments: i.e.,

$$\operatorname{cov}_t(R_{t+1}^d, m_{t+1}^d) = 0,$$

and

$$\operatorname{cov}_t\left(\frac{R_{t+1}^f S_{t+1}}{S_t}, m_{t+1}^d\right) = 0.$$

Then Equations 1 and 2 imply that

$$E_t\left(R_{t+1}^f \frac{S_{t+1}}{S_t}\right) = E_t\left(R_{t+1}^d\right). \tag{3}$$

We further assume that R_{t+1}^f, R_{t+1}^d and S_{t+1}/S_t are multivariate log-normal random variables. Hence Equation 3 can be rewritten as

$$\begin{aligned} & E_t\left(r_{t+1}^f + \Delta s_{t+1}\right) \\ & \quad + \frac{1}{2}\left[\operatorname{var}_t(r_{t+1}^f) + 2\operatorname{cov}_t(r_{t+1}^f, \Delta s_{t+1}) + \operatorname{var}_t(\Delta s_{t+1})\right] \\ & = E_t(r_{t+1}^d) + \frac{1}{2} Var_t(r_{t+1}^d), \end{aligned} \tag{4}$$

where $\Delta s_{t+1} = \log(S_{t+1}/S_t)$ and $r_{t+1}^i = \log(R_{t+1}^i)$ for $i = \{d, f\}$.

We define that

$$\begin{aligned} \rho_{t+1} = {} & \frac{1}{2}\operatorname{var}_t(r_{t+1}^d) - \frac{1}{2}\operatorname{var}_t(r_{t+1}^f) \\ & - \operatorname{cov}_t(r_{t+1}^f, \Delta s_{t+1}) - \frac{1}{2}\operatorname{var}_t(\Delta s_{t+1}), \end{aligned}$$

and we obtain the UEP condition:

$$E_t(\Delta s_{t+1}) = E_t(r_{t+1}^d) - E_t(r_{t+1}^f) + \rho_{t+1}. \tag{5}$$

Equation 5 shows that $E_t(r^d_{t+1}) - E_t(r^f_{t+1}) > 0$ implies that $E_t(\Delta s_{t+1}) > 0$: i.e., when the domestic stock market outperforms the foreign stock market, the domestic currency will depreciate. As the domestic stock market offers higher expected returns, a domestic investor suffers a loss when investing abroad, and therefore should be compensated by the expected capital gain that occurs when the foreign currency appreciates.

3 | ECONOMETRIC FRAMEWORK

3.1 | In-sample predictive regression models

This paper studies the predictability of daily nominal exchange rate movements based on stock return differentials. It is important to emphasize that the UEP condition suggests a contemporaneous relationship between exchange rate movements and stock return differentials. However, the purpose of this work is not to formally test the UEP condition in Equation 5, but rather to investigate the predictive content of stock return differentials for exchange rate movements, which is motivated by the UEP condition. That is, we aim to examine a possible lead–lag relationship between stock return differentials and exchange rate changes because it may take time to rebalance the portfolio.

We consider the following 1-day-ahead predictive regression model for in-sample tests:

$$s_{t+1} - s_t = \alpha + \beta x_t + u_{t+1}, \tag{6}$$

where s_t is the (log) nominal exchange rate, measured as the domestic currency cost of the USD. Hence an increase in s_t represents a depreciation of the domestic currency against the USD. The predictor $x_t = \Delta sp_t - \Delta sp^*_t$ is the stock return differential, where sp_t is the (log) stock price index of the domestic country and sp^*_t denotes the (log) stock price in the foreign country (i.e., the USA in our paper). We test the null hypothesis of no predictive power for future exchange rate movements: $\beta = 0$ against $\beta \neq 0$. That is, we evaluate the in-sample predictability of x_t using a t-statistic corresponding to $\hat{\beta}$, with Newey–West robust heteroskedasticity and autocorrelation consistent (HAC) standard errors.

3.2 | Out-of-sample forecasts

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

$$s_{t+h} - s_t = \alpha + \beta x_t + u_{t+h}. \tag{7}$$

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

$$\hat{s}_{t+h} = s_t + \hat{\alpha}^h_t + \hat{\beta}^h_t x_t, t = R, R+1, \ldots, T-h, \tag{8}$$

where $\hat{\alpha}^h_t$ and $\hat{\beta}^h_t$ are estimated by the rolling scheme with a window width of R. For a given rolling window width R, $\hat{\alpha}^h_t$ and $\hat{\beta}^h_t$ are calculated as follows:

$$\hat{\beta}^h_t = \frac{\sum_{i=t-R+h+1}^{t}(x_{i-h} - \bar{x}_{t-h})(y^h_i - \bar{y}^h_t)}{\sum_{i=t-R+h+1}^{t}(x_{i-h} - \bar{x}_{t-h})^2}, \tag{9}$$

$$\hat{\alpha}^h_t = \bar{y}_t - \hat{\beta}_t \bar{x}_{t-h}, \tag{10}$$

$$\bar{x}_{t-h} = \frac{\sum_{i=t-R+1}^{t-h} x_i}{R-h}, \tag{11}$$

$$\bar{y}^h_t = \frac{\sum_{i=t-R+h+1}^{t} y^h_i}{R-h}, \tag{12}$$

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

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

$$e^2_{t+h}(\mathcal{M}^{\text{RW}}) = (s_{t+h} - s_t)^2, \tag{13}$$

$$e^2_{t+h}(\mathcal{M}^{\text{SRD}}) = \left[s_{t+h} - s_t - \left(\hat{\alpha}^h_t + \hat{\beta}^h_t x_t\right)\right]^2. \tag{14}$$

To evaluate out-of-sample forecasting accuracy, we calculate the average of the h-step-ahead squared prediction errors in Equations 13 and 14 for the out-of-sample period, and denote them as MSPE($\mathcal{M}^{\text{RW}}$) and MSPE($\mathcal{M}^{\text{SRD}}$), respectively. We then compute the MSPE ratio as

$$\text{MSPE ratio} = \frac{\text{MSPE}(\mathcal{M}^{\text{SRD}})}{\text{MSPE}(\mathcal{M}^{\text{RW}})}.$$

Clearly, if the stock return differential has a lower MSPE than the no-change forecast from the random walk model, then the MSPE ratio will be less than one.

To assess whether MSPE($\mathcal{M}^{\text{SRD}}$) is significantly less than MSPE($\mathcal{M}^{\text{RW}}$), we test the following null hypothesis against the alternative hypothesis that the suggested model is more accurate than the driftless random walk model:

$$H_0 : \text{MSPE}(\mathcal{M}^{\text{SRD}}) = \text{MSPE}(\mathcal{M}^{\text{RW}}),$$
$$H_1 : \text{MSPE}(\mathcal{M}^{\text{SRD}}) < \text{MSPE}(\mathcal{M}^{\text{RW}}).$$

We consider the Diebold and Mariano (1995) test statistic (DM):

$$\text{DM} = \frac{\sqrt{P}\bar{d}}{\sqrt{\hat{\Omega}}},$$

where $\bar{d} = P^{-1}\sum_t \hat{d}_{t+h}$, $\hat{d}_{t+h} = (\hat{u}^{\text{RW}}_{t+h})^2 - (\hat{u}^{\text{SRD}}_{t+h})^2$, and $\hat{u}^{\text{RW}}_{t+h}$ and $\hat{u}^{\text{SRD}}_{t+h}$ are forecasting errors for the restricted and unrestricted models, respectively. Moreover, $\hat{\Omega}$ is a consistent estimator of the long-run variance of $\hat{d}_{t+h}$. As a complement, we also consider the Clark and West (2007) MSPE-adjusted test statistics (CW):

$$\text{CW} = \frac{\sqrt{P}\bar{f}}{\sqrt{\hat{V}}},$$

where $\bar{f} = P^{-1}\sum_t \hat{f}_{t+h}$, $\hat{f}_{t+h} = (\hat{u}^{\text{RW}}_{t+h})^2 - [(\hat{u}^{\text{SRD}}_{t+h})^2 - (\hat{y}^{\text{RW}}_{t+h} - \hat{y}^{\text{SRD}}_{t+h})^2]$, and $\hat{V}$ is the sample variance of $(\hat{f}_{t+k} - \bar{f})$.

As pointed out by Rogoff and Stavrakeva (2008), previous studies tend to report some "best" out-of-sample forecasting results without showing the robustness to the choice of the rolling window R. However, the empirical result may depend on the choice of the rolling window R. If the researcher considers a variety of rolling windows and reports the empirical results based on the "best" rolling window (i.e., the rolling window that generates the smallest MSPEs), then the tests based on the chosen rolling window do not have the correct size (for details see, e.g., Inoue, Jin, & Rossi, 2017; Pesaran & Timmermann, 2007; Rossi & Inoue, 2012). To address this data-snooping issue, we follow White (2000) and Rossi and Inoue (2012) to consider rolling supremum-type Diebold–Mariano (sup-DM) and supremum-type Clark–West (sup-CW) statistics as follows:

$$\text{sup-DM} = \max_{R\in[\underline{R},\ldots,\overline{R}]} \text{DM}(R),$$
$$\text{sup-CW} = \max_{R\in[\underline{R},\ldots,\overline{R}]} \text{CW}(R),$$

where DM(R) and CW(R) are the DM and CW statistics under window size R, and $\underline{R}$ and $\overline{R}$ are the smallest and largest window sizes, respectively. The critical values for the sup-statistics are obtained by using the bootstrap method.

4 | DATA

We examine daily exchange rate predictability with stock return differentials using the seven most-traded currencies, the USD, EUR, JPY, GBP, AUD, CHF, and CAD. The USD is used as the numeraire. The nominal exchange rate data are obtained from Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis, and stock prices are collected from Yahoo Finance. The sample periods all end on March 31, 2017, but the starting points vary by country because of equity data availability. Stock returns are measured by changes in the (log) representative stock price index in each country, including the Euronext 100 Index (2000/1/3–2017/3/31), Nikkei 225 index (1984/1/5–2017/3/31), FTSE 100 index (1984/1/4–2017/3/31), Swiss Market Index (1990/11/13–2017/3/31), S&P/ASX 200 index (1992/11/24–2017/3/31), and S&P TSX Composite index (1979/7/2–2017/3/31). The S&P 500 Index is used as the measure of general aggregate stock market prices in the USA. Table 1 provides details on data sources, associated codes, and sample periods. For consistency, we convert American (USD) quotations into European quotations for the EUR, GBP, and AUD, so that an increase in the exchange rate represents a depreciation of the

TABLE 1 Data sources

Variable name	Source	Code
USA		
S&P 500 Index	Yahoo Finance	GSPC
EU: from 2000-1-3 to 2017-3-31 (T = 4267)		
Nominal exchange rates	FRED	DEXUSEU
Euronext 100 Index	Yahoo Finance	N100
Japan: from 1984-1-5 to 2017-3-31 (T = 7882)		
Nominal exchange rates	FRED	DEXJPUS
Nikkei 225 Index	Yahoo Finance	N225
UK: from 1984-1-4 to 2017-3-31 (T = 8206)		
Nominal exchange rates	FRED	DEXUSUK
FTSE 100 Index	Yahoo Finance	FTSE
Switzerland: from 1990-11-13 to 2017-3-31 (T = 6455)		
Nominal exchange rates	FRED	DEXSZUS
Swiss Market Index	Yahoo Finance	SSMI
Australia: from 1992-11-24 to 2017-3-31 (T = 5965)		
Nominal exchange rates	FRED	DEXUSAL
S&P/ASX 200 Index	Yahoo Finance	AXJO
Canada: from 1979-7-2 to 2017-3-31 (T = 9410)		
Nominal exchange rates	FRED	DEXCAUS
S&P TSX Composite Index	Yahoo Finance	GSPTSE

TABLE 2 Descriptive statistics of the daily changes in exchange rates and stock returns

		Δs_t				Δsp_t			
	Obs.	**Mean**	**Max.**	**Min.**	**SD**	**Mean**	**Max.**	**Min.**	**SD**
Australia	5965	−0.0000	0.0821	−0.0770	0.0078	0.0002	0.0903	−0.1026	0.0099
Canada	9410	0.0000	0.0381	−0.0507	0.0045	0.0002	0.0937	−0.1180	0.0098
Switzerland	6455	−0.0000	0.0889	−0.1302	0.0073	0.0003	0.1576	−0.0907	0.0117
EU	4267	−0.0000	0.0300	−0.0462	0.0064	−0.0000	0.1238	−0.0895	0.0138
UK	8206	0.0000	0.0817	−0.0459	0.0064	0.0002	0.1111	−0.1303	0.0111
Japan	7882	−0.0001	0.0361	−0.0563	0.0069	0.0001	0.1323	−0.1614	0.0149
USA	9410					0.0003	0.1042	−0.2290	0.0112

Note. Values listed as 0.0000 are less than 0.00005.

domestic currency. Descriptive statistics are provided in Table 2.

5 | EMPIRICAL RESULTS

5.1 | In-sample predictive regression results

The in-sample predictive regression results based on Equation 6 are reported in Table 3. The Bartlett kernel is used to construct the Newey–West HAC standard errors, where the truncation parameter is determined by rounding $0.75T^{1/3}$ to the nearest integer. Figure 1 plots the scatter plots with fitted regression lines.

All of the estimates of β are statistically significant at the 5% level except for Switzerland. As the estimate of β for the CHF–USD is negative, it is statistically insignificant at any conventional significance level. It is worth noting that the coefficient estimates for four out of the six currencies (EUR, GBP, AUD, and CAD) are consistent with UEP, i.e., a higher return in the domestic stock market is associated with a depreciation of the domestic currency. The estimation results for the JPY exchange rate are at odds with the prediction of the UEP. This finding, however, agrees with that reported by Hau and Rey (2006). As discussed in Hau and Rey, the reason for the inconsistency may be because international portfolio flows mainly involve equities, whereas in Japan they mainly involve bonds. Moreover, a negative correlation may suggest return-chasing behavior by investors, whereby investors often increase their holdings in markets that have recently outperformed other markets (see, e.g., Bohn & Tesar, 1996; Chabot, Ghysels, & Jagannathan, 2014; Griffin et al., 2004). Such behavior would lead the domestic currency to appreciate during the next trading day when the domestic stock market outperforms the US market. In summary, although there is no overwhelming evidence in support of the UEP condition, our in-sample analysis suggests that the stock return differential has in-sample explanatory power for currency movements.

TABLE 3 In-sample predictability

	$\hat{\beta}$	**SE**	***t*-stat.**	**Pr(> |*t*|)**
Australia	0.084	0.020	4.23	0.00***
Canada	0.040	0.011	3.56	0.00***
Switzerland	−0.009	0.011	−0.87	0.38
EU	0.040	0.014	2.97	0.00***
UK	0.022	0.011	2.06	0.04**
Japan	−0.018	0.006	−3.09	0.00***

Note. The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + u_{t+1}$, where $s_{t+1} - s_t$ and x_t denote exchange rate changes and stock return differentials. We test the null hypothesis that $\beta = 0$ against $\beta \neq 0$. The *t*-statistics are computed using Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Asterisks indicate significance at the *10%, **5% and ***1% levels.

5.2 | Out-of-sample forecasting performance

It is well known that models that fit well in-sample are not guaranteed to have good out-of-sample forecasting performance. In fact, future exchange rates have been shown to be extremely difficult to forecast out-of-sample. We now move our focus to out-of-sample tests to evaluate exchange rate predictability.

As a preliminary investigation, we report the out-of-sample forecasting results for the case of $R = 0.4T$ in Table 4. We consider forecasting horizons of 1, 3, 5, and 20 days. The table shows results including the MSPE ratios, i.e., $\frac{\text{MSPE}(\mathcal{M}^{\text{SRD}})}{\text{MSPE}(\mathcal{M}^{\text{RW}})}$, the out-of-sample R^2 (OOS-R^2) statistics proposed by Campbell and Thompson (2008), and the corresponding bootstrap *p*-values of the Diebold and Mariano (1995) test statistics (DM-Boot) and the Clark and West (2007) test statistics (CW-Boot). As the Diebold–Mariano test is a minimum mean square forecast error test, rejecting the null hypothesis thus results in the conclusion that the proposed model has a better out-of-sample forecasting performance. In the case of nested models, Clark and West (2006) document that the Diebold–Mariano test is poorly sized and, thus, the adjusted mean square

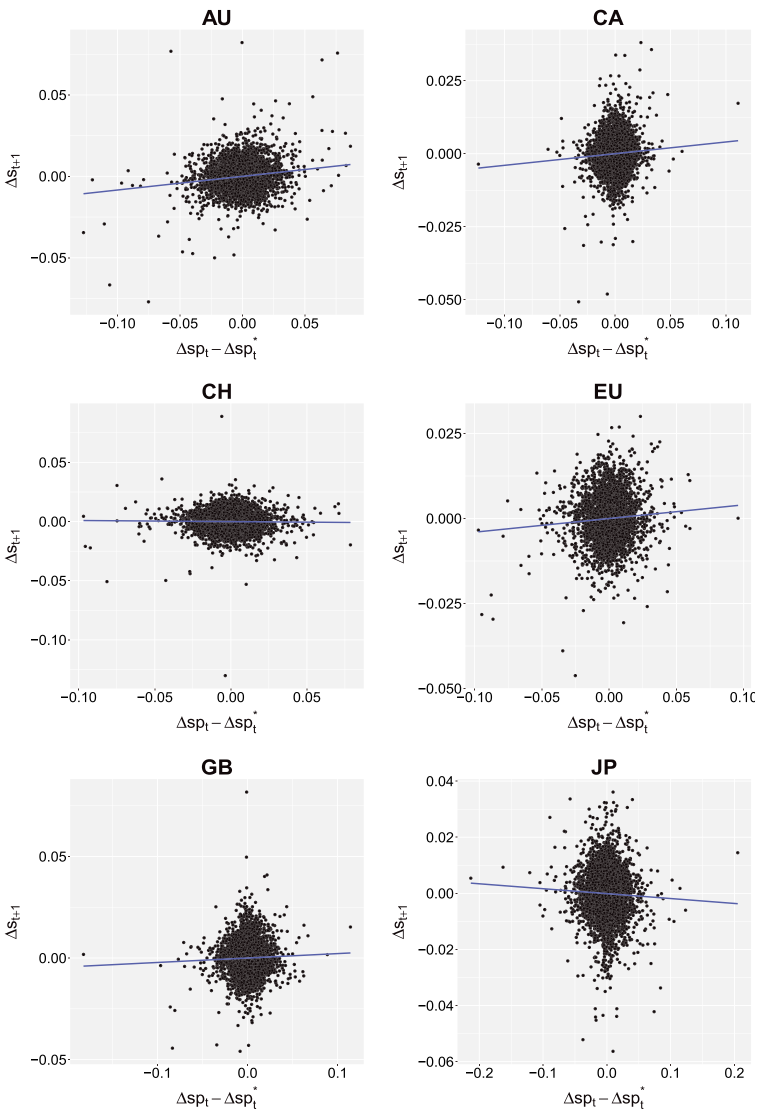

FIGURE 1 Scatter plots: stock return differentials ($\Delta sp_t - \Delta sp_t^*$) versus exchange rate changes (Δs_{t+1}) [Colour figure can be viewed at wileyonlinelibrary.com]

prediction error (MSPE-Adj) test proposed by Clark and West (2007) is able to yield a more accurate size. However, Rogoff and Stavrakeva (2008) point out that the role of the MSPE-Adj test is to test whether the dependent variable follows a random walk model. In other words, a significant MSPE-Adj test statistic does not always imply that the proposed model outperforms the random walk model. Therefore, we report both test statistics to check the robustness of the empirical results.

Clearly, for the case $h = 1$ (1-day-ahead forecast), the forecasts for exchange rate movements based on stock return differentials produce lower MSPEs than the MSPEs produced by the random walk model, for Australia, Canada, European Union, the UK, and Japan. Stock return differentials may reduce the MSPEs by between 0.2% (for Japan) and 3.1% (for Australia). The reductions may be small, but it is worth noting that daily exchange rate movements are quite noisy. The bootstrap *p*-values for the Diebold–Mariano tests are statistically significant for five out of six currencies (Australia, Canada, and the UK at the 1% level, and European Union and Japan at the 5% level). The results for the Clark–West tests provide even stronger support for exchange rate predictability: it is statistically significant at the 1% level for Australia, Canada, European Union, and the UK, and significant at the 5% level for Japan. The only exchange rate that unfortunately has poor out-of-sample forecasting performance is the Swiss franc exchange rate. Clearly, the out-of-sample test results show that five of the six currency pairs that we investigate provide evidence of 1-day-ahead exchange rate predictability, which is consistent with the above in-sample analysis. For longer horizons ($h = 3$ and 5), only three out of six currencies are found to be statistically significant (Australia, European Union, and the UK). There is no predictive

TABLE 4 Out-of-sample forecasting results: $R = 0.4T$

	MSPE ratio	OOS−R^2	DM-Boot	CW-Boot	MSPE ratio	OOS−R^2	DM-Boot	CW-Boot
	Australia				Canada			
$h = 1$	0.9690	0.0310	0.000***	0.000***	0.9951	0.0049	0.001***	0.001***
3	0.9934	0.0066	0.000***	0.000***	1.0015	−0.0015	0.746	0.748
5	0.9965	0.0035	0.007***	0.000***	1.0028	−0.0028	0.933	0.924
20	1.0130	−0.0130	0.948	0.831	1.0114	−0.0114	0.895	0.910
	Switzerland				EU			
$h = 1$	1.0038	−0.0038	0.683	0.388	0.9959	0.0041	0.016**	0.000***
3	1.0022	−0.0022	0.664	0.552	0.9980	0.0020	0.030**	0.004***
5	1.0024	−0.0024	0.532	0.472	0.9994	0.0006	0.098*	0.021**
20	1.0060	−0.0060	0.367	0.370	1.0066	−0.0066	0.283	0.281
	UK				Japan			
$h = 1$	0.9960	0.0040	0.001***	0.000***	0.9980	0.0020	0.035**	0.028**
3	0.9998	0.0002	0.085*	0.049**	1.0013	−0.0013	0.610	0.428
5	0.9996	0.0004	0.052**	0.029**	1.0029	−0.0029	0.819	0.804
20	1.0060	−0.0060	0.891	0.893	1.0123	−0.0123	0.923	0.903

Note. The MSPE ratio is $\frac{\text{MSPE}(\mathcal{M}^{\text{SRD}})}{\text{MSPE}(\mathcal{M}^{\text{RW}})}$. OOS-$R^2$ is the out-of-sample R^2 statistics proposed by Campbell and Thompson (2008). DM-Boot and CW-Boot are the corresponding bootstrap p-values of the test statistics proposed by Diebold and Mariano (1995) and Clark and West (2007), respectively. Values listed as 0.000 are less than 0.0005. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

power for 20-day-ahead forecasts for all currencies considered. In sum, using stock return differentials as a predictor, we have found a strong forecasting performance for short-run (1-day-ahead) exchange rate movements, while the predictive power is limited for those horizons greater than 3 days. The lack of predictive power for longer horizons is reasonable: If the predictive power of stock return differentials on exchange rates is based on the portfolio rebalancing (or trend-chasing) behavior, then the predictive ability should appear more at short horizons because the behavior is associated with high-frequency trading.

The above results are based on a window size $R = 0.4T$. As indicated in Rossi and Inoue (2012), there are two types of concerns regarding the choice of R. One concern is that selecting an ad hoc value of R without trying alternative values causes a low-power problem. That is, it is possible that researchers may fail to find empirical evidence in favor of predictive ability because the window size was

TABLE 5 Sup Diebold–Mariano test

	Sup-DM	10%	5%	1%	Sup-DM	10%	5%	1%
	Australia				Canada			
$h = 1$	2.75***	1.20	1.55	2.14	2.39***	1.31	1.65	2.16
3	1.38**	1.06	1.29	1.84	0.03	1.09	1.32	1.80
5	1.16*	1.08	1.29	1.84	−0.38	1.12	1.39	1.95
20	−1.47	1.16	1.53	2.45	−0.55	1.33	1.68	2.24
	Switzerland				EU			
$h = 1$	0.72	1.24	1.61	2.28	2.51***	1.21	1.53	2.02
3	−0.31	1.03	1.33	1.71	0.67	0.99	1.19	1.74
5	−0.17	1.04	1.40	1.79	0.37	1.04	1.30	1.67
20	−0.11	1.17	1.47	2.15	−0.32	1.17	1.50	2.09
	UK				Japan			
$h = 1$	2.75***	1.29	1.59	2.43	1.15	1.55	1.85	2.44
3	1.59**	1.07	1.36	1.93	0.77	1.33	1.61	2.07
5	2.18***	1.14	1.40	1.96	1.16	1.37	1.59	2.32
20	2.65***	1.31	1.70	2.45	1.09	1.53	1.97	2.87

Note. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

TABLE 6 Sup Clark–West test

	Sup-CW	10%	5%	1%	Sup-CW	10%	5%	1%
	Australia				Canada			
$h = 1$	4.92***	1.88	2.16	2.77	3.60***	1.94	2.21	2.82
3	3.76***	1.60	1.83	2.21	0.52	1.61	1.87	2.26
5	3.47***	1.59	1.82	2.25	0.50	1.63	1.94	2.51
20	0.59	1.67	1.96	2.82	0.18	1.88	2.15	2.69
	Switzerland				EU			
$h = 1$	3.00***	1.97	2.26	2.95	4.54***	1.88	2.13	2.67
3	0.53	1.55	1.80	2.35	2.49***	1.49	1.70	2.09
5	−0.01	1.62	1.91	2.39	2.25***	1.51	1.71	1.95
20	0.16	1.70	1.99	2.63	0.71	1.62	1.89	2.50
	UK				Japan			
$h = 1$	4.73***	1.90	2.18	2.91	2.53*	2.38	2.68	3.20
3	2.24**	1.59	1.86	2.44	1.91	1.95	2.22	2.73
5	2.87***	1.63	1.91	2.48	1.88	1.96	2.20	2.86
20	3.10***	1.77	2.06	2.86	1.73	2.21	2.60	3.54

Note. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

either too small or too large to capture it. However, there may exist data-snooping bias as suggested in White (2000), which causes an oversize problem. In particular, Rogoff and Stavrakeva (2008) argue that most previous studies on exchange rate predictability fail to check for robustness to the time period estimated. Therefore, we further consider an out-of-sample forecast exercise that is robust to data snooping over the length of the estimation window using supremum-type out-of-sample test statistics.

The supremum-type Diebold–Mariano (sup-DM) and Clark–West (sup-CW) statistics are calculated over the window size $R \in [0.15T, 0.85T]$. It is worth noting that it includes nearly 8,000 out-of-sample observations for the largest sample (CAD/USD, $T = 9,410$), with the smallest window size $\underline{R}$ equaling $0.15T$. Moreover, even for the smallest sample observations (EUR/USD, $T = 4,267$) with the largest rolling window size ($\overline{R} = 0.85T$), the out-of-sample period still contains more than 600 observations.

The results for the sup-DM and sup-CW statistics are reported in Tables 5 and 6. As the desired distributions of the sup-type statistics are unknown, the critical values are obtained by the bootstrap method using the following steps. (1) Under the null of a random walk, obtain bootstrap data from the exchange rate returns: $\Delta s_t = s_t - s_{t-1}$. (2) Then estimate the UEP model on the bootstrap data and actual relative equity returns using the various rolling windows. (3) Find the sup-type statistics out of all windows for the bootstrap data, and denote them as sup-DM* and sup-CW*. (4) Perform steps (2)–(4) 1,000 times and save the sup-type statistics for each replication. (5) Using the resulting bootstrap distribution of sup-DM* and sup-CW* to obtain the critical values.

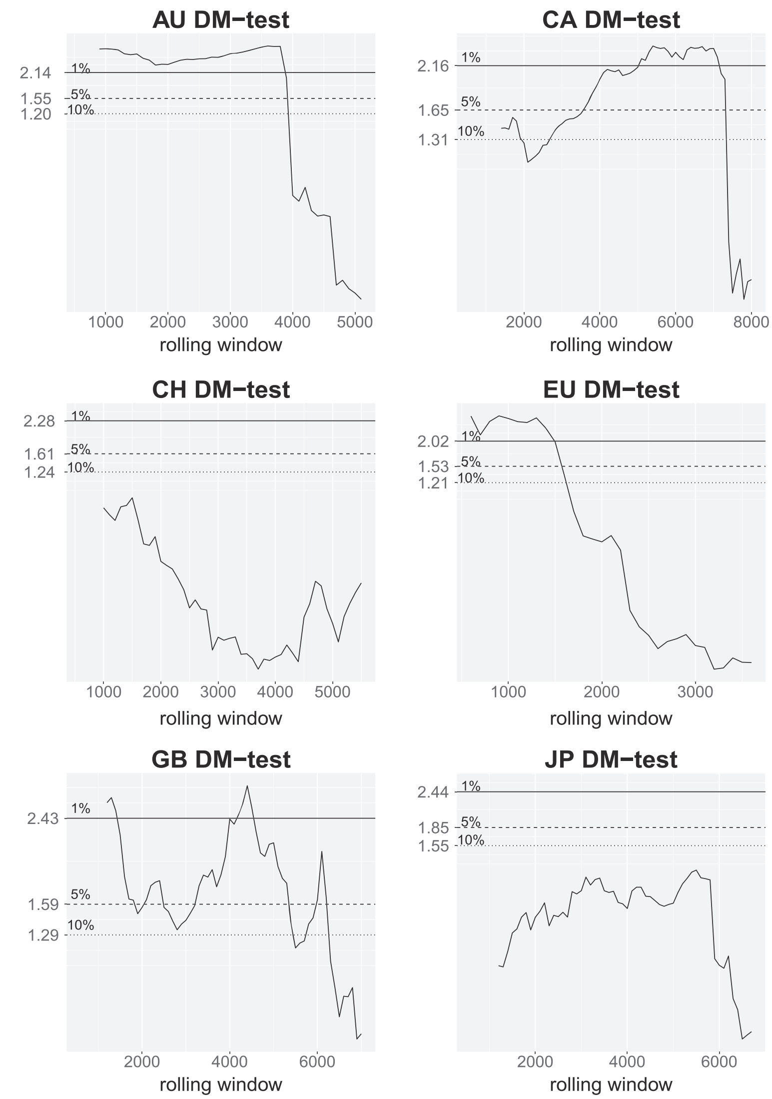

FIGURE 2 The estimated Diebold–Mariano (DM) test statistic for comparing the UEP model with the random walk for the window sizes considered (reported on the x-axis), together with 1%, 5%, and 10% bootstrap critical values of the sup-DM test statistic. The test rejects when the largest value of the DM statistic is above the critical value line. The forecast horizon is $h = 1$

We can observe in Table 5 that for short-horizon forecasts ($h = 1$), the sup-DM statistics suggest that the UEP model significantly outperforms the random walk for Australia, Canada, EU, and UK at the 5% significance level. For Japan and Switzerland, the stock return differentials fail to provide good forecasts of future exchange rate movements. In Table 6, the empirical results based on the sup-CW statistics provide stronger support for the short-run exchange rate predictability of the stock return differentials. For $h = 1$, the UEP model significantly outperforms the random walk model for Australia, Canada, Switzerland, EU, and UK at the 1% significance level, while the sup-CW statistic for Japan indicates statistical significance at the 10% level. For Australia, EU, and UK, predictability is also found at longer forecasting horizons ($h = 3$ and 5). Figures 2 and 3 show the Diebold–Mariano

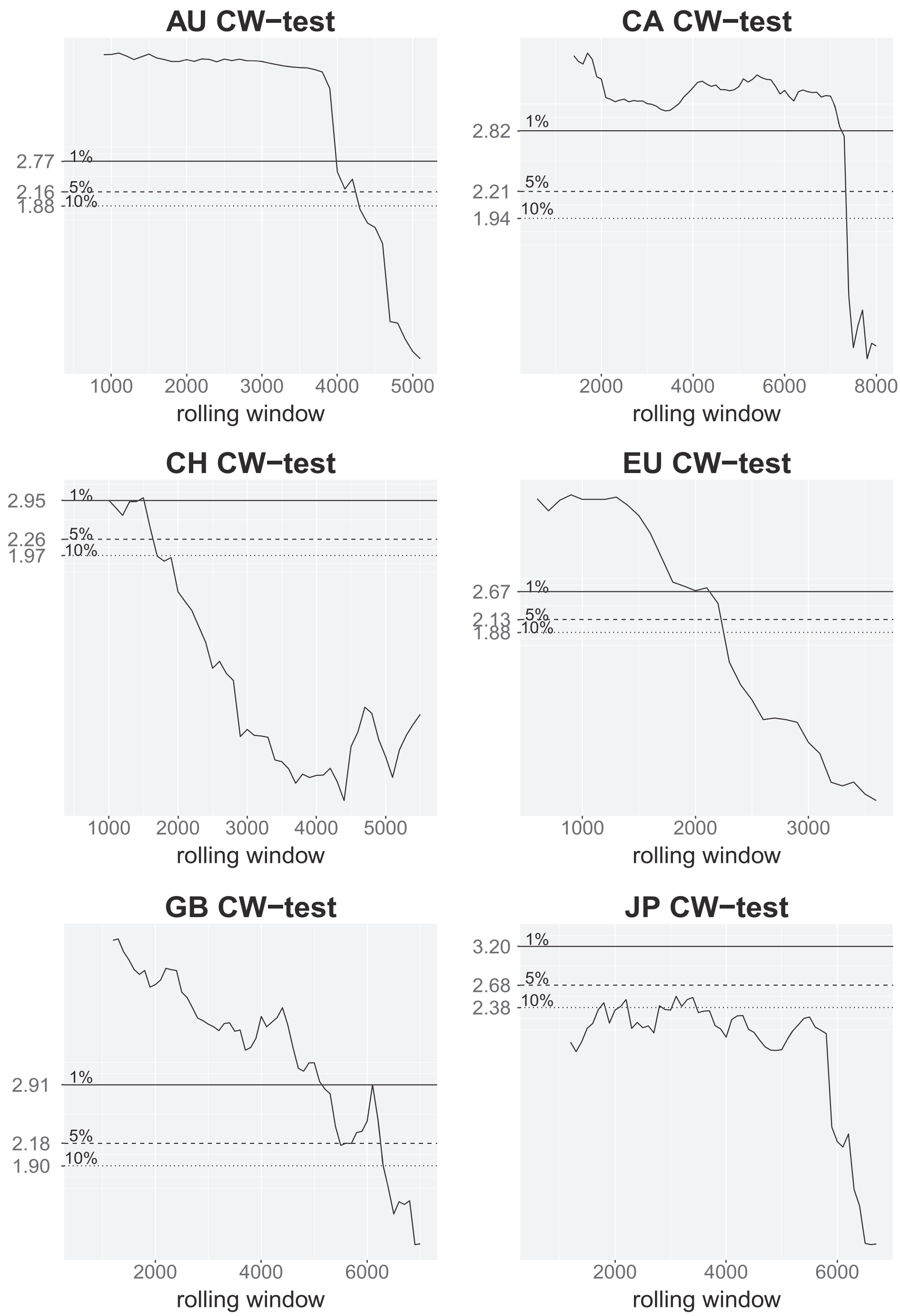

FIGURE 3 The estimated Clark–West (CW) test statistic for comparing the UEP model with the random walk for the window sizes considered (reported on the *x*-axis), together with 1%, 5%, and 10% bootstrap critical values of the sup-CW test statistic. The test rejects when the largest value of the CW statistic is above the critical value line. The forecast horizon is $h = 1$

and the Clark–West test statistics for the window sizes we consider. Note that the tests reject the random walk model when the largest value of the test statistic is above the critical value line.

To sum up, the out-of-sample forecasting results show evidence that the stock return differential may help to predict the nominal exchange rates of major currencies out-of-sample, using 1-day-ahead forecasts, and the results are robust to data mining over different window sizes.

6 | ROBUSTNESS CHECKS

To check the robustness of our empirical results, we consider several modifications. In the following robustness checks, we will focus only on 1-day-ahead forecasts ($h = 1$).

6.1 | Other benchmark models

The random walk model is used as the benchmark for out-of-sample forecasting performance. Suppose that there are short-term swings in the daily exchange rates. Then, the random walk model will underperform because it may fail to capture the short-term swings. We thus consider alternative benchmark models that may better capture the possible short-term swings, using a conventional autoregressive model of order one, AR(1) model. For the in-sample test, we test $\beta = 0$ in the following predictive model:

$$s_{t+1} - s_t = \alpha + \rho(s_t - s_{t-1}) + \beta x_t + u_{t+1},$$

where x_t is the stock return differential. The nested models for out-of-sample forecast evaluation are

$$\text{Model 1}: \; s_{t+1} - s_t = \alpha + \rho(s_t - s_{t-1}) + u_{t+1},$$
$$\text{Model 2}: \; s_{t+1} - s_t = \alpha + \rho(s_t - s_{t-1}) + \beta x_t + u_{t+1}.$$

Clearly, Model 2 is an unrestricted model, while Model 1 is a restricted model, which suggests that stock return differentials do not provide any predictive content. We test whether Model 2 has better forecasting performance than Model 1 using sup-DM and sup-CW test statistics.

Tables 7 and 8 report the corresponding empirical results, which are quantitatively and qualitatively similar to the main empirical results. The results show that short-term swings play a less significant role in exchange rate movements, and provide evidence of exchange rate predictability using stock return differentials.

6.2 | Forecasting the level of the exchange rate

Although it is common to forecast exchange rate changes in the exchange rate forecasting literature, policymakers and economists may care about the level of the predictand rather than the percentage change in the predictand, as

TABLE 7 In-sample predictability: nested AR(1)

	$\hat{\beta}$	SE	t-stat.	Pr(> |t|)	$\hat{\rho}$	SE	t-stat.	Pr(> |t|)
Australia	0.084	0.020	4.21	0.00***	−0.039	0.040	−0.97	0.33
Canada	0.040	0.011	3.53	0.00***	0.009	0.019	0.50	0.62
Switzerland	−0.011	0.011	−1.06	0.29	0.020	0.019	1.04	0.30
EU	0.040	0.014	2.98	0.00***	0.000	0.014	−0.01	0.99
UK	0.021	0.011	1.92	0.06*	0.047	0.014	3.29	0.00***
Japan	−0.018	0.006	−3.07	0.00***	0.016	0.017	0.92	0.36

Note. The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + \rho(s_t - s_{t-1}) + u_{t+1}$, where $s_{t+1} - s_t$, x_t denote exchange rate changes and stock return differentials. The t-statistics are computed using Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Asterisks indicate significance at the *10%, **5% and ***1% levels.

TABLE 8 Robustness check: nested AR(1) benchmark

	Sup-DM	10%	5%	1%	Sup-CW	10%	5%	1%
Australia	3.31***	1.20	1.53	2.17	5.65***	1.90	2.26	2.79
Canada	2.39***	1.17	1.46	1.96	3.48***	1.95	2.24	2.82
Switzerland	1.35*	1.15	1.52	2.19	3.65***	1.98	2.32	2.93
EU	2.75***	1.13	1.49	2.09	4.53***	1.96	2.26	2.81
UK	2.82***	1.20	1.53	2.28	4.84***	1.95	2.27	2.78
Japan	1.23*	1.21	1.47	2.13	2.74**	1.97	2.25	2.88

Note. The forecast horizon is set to be $h = 1$. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5% and ***1% levels.

TABLE 9 Robustness check: forecasting the level

	Sup-DM	10%	5%	1%	Sup-CW	10%	5%	1%
Australia	2.89***	1.18	1.53	2.00	4.42***	1.81	2.09	2.71
Canada	2.41***	1.28	1.60	2.11	3.52***	1.98	2.28	2.88
Switzerland	0.85	1.14	1.58	2.21	3.33***	1.93	2.24	2.82
EU	2.40***	1.27	1.54	2.00	4.35***	1.83	2.12	2.68
UK	2.76***	1.32	1.60	2.25	4.58***	1.93	2.21	2.89
Japan	1.35	1.95	2.27	2.80	2.69*	2.45	2.73	3.16

Note. The forecast horizon is set to be $h = 1$. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

TABLE 10 In-sample predictability controlling for oil price changes

	$\hat{\beta}$	SE	*t*-stat.	Pr(> |*t*|)	$\hat{\gamma}$	SE	*t*-stat.	Pr(> |*t*|)
Australia	0.084	0.020	4.19	0.00***	−0.003	0.006	−0.49	0.62
Canada	0.048	0.013	3.73	0.00***	−0.012	0.002	−5.00	0.00***

Note. The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + \gamma \Delta \mathrm{op}_t + u_{t+1}$, where $s_{t+1} - s_t$, x_t and $\Delta \mathrm{op}_t$ denote exchange rate changes, stock return differentials, and changes in oil prices. The *t*-statistics are computed using Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Asterisks indicate significance at the *10%, **5% and ***1% levels.

Baumeister and Kilian (2012) point out. We now change our objective to forecasting the level of the exchange rates.

The predictive model is

$$\frac{S_{t+1} - S_t}{S_t} = \alpha + \beta x_t + u_{t+1}, \tag{15}$$

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

$$\frac{\widehat{S}_{t+1} - S_t}{S_t} = \tilde{\alpha}_t + \tilde{\beta}_t x_t, t = R, R+1, \ldots, T-1, \tag{16}$$

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

$$\widehat{S}_{t+1} = S_t \times \left(1 + \tilde{\alpha}_t + \tilde{\beta}_t x_t\right). \tag{17}$$

The empirical results are reported in Table 9. Obviously, the evidence also shows a strong predictability when forecasting the level of the exchange rate directly.

6.3 | Commodity currencies

Chen and Rogoff (2003) have shown a close link between exchange rates and commodity prices for commodity currencies via in-sample fit. Ferraro, Rogoff, and Rossi (2015) further show that lagged crude oil price changes may have predictive ability for daily CAD–USD exchange rates when certain rolling windows are employed; that is, there exists a relationship between the lagged oil price changes and exchange rate movements.

Therefore, for commodity currencies in our sample countries (Australia and Canada), we check the robustness of the in-sample and out-of-sample predictive power by controlling for oil price changes. The following is the predictive regression model for in-sample tests when oil price changes are controlled:

$$s_{t+1} - s_t = \alpha + \beta x_t + \gamma \Delta \mathrm{op}_t + u_{t+1}, \tag{18}$$

where $\Delta \mathrm{op}_t$ is the first difference of the logarithm of oil price.[2] For out-of-sample predictive power, we evaluate the one-step-ahead forecasting accuracy of the following nested models:

$$\text{Model 1}: \; s_{t+1} - s_t = \alpha + \gamma \Delta \mathrm{op}_t + u_{t+1},$$

$$\text{Model 2}: \; s_{t+1} - s_t = \alpha + \beta x_t + \gamma \Delta \mathrm{op}_t + u_{t+1}.$$

We then test the null hypothesis of equal MSPEs against the alternative hypothesis that Model 2 has a smaller MSPE than Model 1. Thus we check whether stock return differentials can provide additional out-of-sample predictive power after controlling for oil price changes.

Table 10 reports the in-sample results. According to the estimates of $\hat{\gamma}$, it is evident that oil price changes play an insignificant role in AUD–USD exchange rate dynamics, but have significant in-sample predictive power for the CAD–USD exchange rate. The results are consistent with Ferraro et al. (2015). Moreover, it can be observed that stock return differentials still have significant forecasting power after accounting for oil prices. Out-of-sample forecasting results are presented in Table 11, which shows that our previous conclusions remain. Clearly, in both in- and out-of-sample tests, stock return differentials have

[2]The daily oil price series is the spot price of West Texas Intermediate (WTI) crude oil, which is obtained from FRED. Daily data on the WTI crude oil price are available after 1984.

TABLE 11 Robustness check: controlling for oil price changes

	Sup-DM	10%	5%	1%	Sup-CW	10%	5%	1%
Australia	2.76***	1.36	1.65	2.31	4.90***	1.79	2.07	2.84
Canada	2.39***	1.32	1.68	2.24	3.63***	1.90	2.17	2.64

Note. The forecast horizon is set to be $h = 1$. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

TABLE 12 In-sample predictability controlling for interest rate differentials

	$\widehat{\beta}$	SE	t-stat.	Pr(> |t|)	$\widehat{\delta}$	SE	t-stat.	Pr(> |t|)
Australia	0.096	0.021	4.62	0.00***	−0.007	0.007	−1.06	0.29
Canada	0.052	0.015	3.42	0.00***	−0.001	0.003	−0.43	0.66
Switzerland	−0.009	0.011	−0.81	0.42	−0.003	0.005	−0.73	0.47
EU	0.041	0.014	3.02	0.00***	−0.003	0.009	−0.36	0.72
UK	0.023	0.011	2.08	0.04**	−0.001	0.005	−0.14	0.89
Japan	−0.018	0.006	−3.22	0.00***	−0.004	0.004	−1.02	0.31

Note. The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + \delta(i_t - i_t^*) + u_{t+1}$, where $s_{t+1} - s_t, x_t$ and $i_t - i_t^*$ denote exchange rate changes, stock return differentials, and interest rate differentials. The t-statistics are computed using Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

TABLE 13 Robustness check: controlling for interest rate differentials

	Sup-DM	10%	5%	1%	Sup-CW	10%	5%	1%
Australia	3.86***	1.22	1.46	1.89	5.19***	1.71	1.97	2.47
Canada	2.71***	1.22	1.54	2.14	3.76***	1.67	1.99	2.76
Switzerland	0.98	1.36	1.63	2.21	3.13***	1.80	2.07	2.61
EU	2.84***	1.36	1.65	2.30	4.60***	1.75	2.09	2.65
UK	2.83***	1.54	1.81	2.23	4.79***	1.91	2.19	2.58
Japan	1.26	1.28	1.64	2.17	2.64**	1.75	2.02	2.68

Note. The forecast horizon is set to be $h = 1$. Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

predictive power for commodity currency exchange rate movements, even after conditioning on oil price changes.

6.4 | Controlling for interest rate differentials

In consideration of the uncovered interest rate parity (UIP) fundamental, we further control for interest rate differentials. The econometric framework is similar to the previous subsection, but oil price changes are replaced by interest rate differentials ($i_t - i_t^*$):

$$\text{Model 1}: \; s_{t+1} - s_t = \alpha + \delta(i_t - i_t^*) + u_{t+1},$$

$$\text{Model 2}: \; s_{t+1} - s_t = \alpha + \beta x_t + \delta(i_t - i_t^*) + u_{t+1},$$

where i_t is the interest rate of the domestic country and i_t^* denotes the US interest rate. The interest rate is measured by the 1-month London Interbank Offered Rate (LIBOR).[3]

[3]The data are obtained from FRED. Note that the LIBOR series based on the AUD and CAD are discontinued after May 31, 2017.

The results are reported in Tables 12 and 13. It is clear that our main findings are robust after controlling for UIP.

7 | EXCHANGE RATE PREDICTABILITY WITH UEP AT MONTHLY FREQUENCY

In our main empirical investigation, we argue that we should focus on daily data when using stock return differentials to forecast exchange rate movements. If exchange rate predictability with UEP comes from high-frequency portfolio rebalancing, we would expect that the evidence will be less significant when lower-frequency data is used. To reexamine our results using a monthly frequency, we convert daily data to end-of-period monthly data; that is, the monthly observation is the observation on the last trading day of the month.

The in-sample results are reported in Table 14, whereas Table 15 shows the out-of-sample sup-DM and sup-CW test statistics. As expected, the estimates of β are mostly

TABLE 14 In-sample predictability with monthly data

	$\hat{\beta}$	SE	t-stat.	Pr(> |t|)
Australia	−0.072	0.062	−1.16	0.25
Canada	−0.005	0.038	−0.12	0.90
Switzerland	0.002	0.058	0.04	0.97
EU	−0.217	0.068	−3.18	0.00***
UK	0.010	0.070	0.14	0.89
Japan	−0.010	0.041	−0.25	0.80

Note. The predictive regression model for in-sample tests is $s_{t+1} - s_t = \alpha + \beta x_t + u_{t+1}$, where $s_{t+1} - s_t$ and x_t denote exchange rate changes and stock return differentials. We test the null hypothesis that $\beta = 0$ against $\beta \neq 0$. The *t*-statistics are computed using Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Asterisks indicate significance at the *10%, **5% and ***1% levels.

TABLE 15 Out-of-sample predictability with monthly data

	Sup-DM	10%	5%	1%	Sup-CW	10%	5%	1%
Australia	0.21	1.43	1.78	2.60	0.65	2.11	2.39	3.14
Canada	−0.21	1.50	1.87	2.51	−0.11	2.07	2.40	3.04
Switzerland	0.27	1.53	1.90	2.60	0.92	2.22	2.55	3.17
EU	0.44	1.42	1.78	2.47	2.74**	2.18	2.58	3.14
UK	1.68*	1.46	1.81	2.50	2.04	2.17	2.53	3.02
Japan	1.04	1.58	1.94	2.52	1.48	2.42	2.80	3.38

Note. The forecast horizon is set to be $h = 1$ (month). Critical values are obtained by the bootstrap method using 1,000 replications. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

statistically insignificant at conventional levels. Moreover, the out-of-sample forecasting ability of all currency pairs is limited. The results are consistent with the findings in Cenedese et al. (2016) that exchange rate movements are in fact unrelated to differentials in country-level equity returns using monthly data.

8 | CONCLUSIONS

Producing a more accurate prediction of short-run exchange rates has posed a difficult ongoing challenge for economists. It is a difficult but not impossible problem. In this study, we use stock return differentials to predict daily exchange rate movements, motivated by the UEP theory. Using exchange rate data on the six most-traded currencies against the US dollar—that is, the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Euro (EUR), British pound (GBP), and Japanese yen (JPY)—we perform both in-sample and out-of-sample forecasting exercises to assess short-run exchange rate predictability.

This paper uncovers a lead–lag relationship between stock and foreign exchange markets. Using a rich set of daily data, we find that for EUR/USD, GBP/USD, AUD/USD, and CAD/USD exchange rates, the domestic currency will depreciate on the next trading day when the domestic stock market outperforms the foreign (US) market, which is consistent with the UEP theory. We also find that at short horizons (1-day-ahead predictions), the stock return differential has both in-sample and out-of-sample forecasting power for all currencies, except for the Swiss franc. Our empirical findings provide evidence that daily exchange rate changes are predictable with stock return differentials. That is, stock markets provide information about exchange rate movements, at least in the case of high-frequency data.

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