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Liquidity yield and exchange rate predictability☆

Shiu-Sheng Chen [a,1], Yu-Hsi Chou [b,1,*]

[a] Department of Economics, National Taiwan University. Social Science Building, No.1, Section 4, Roosevelt Road, Taipei, Taiwan
[b] Department of Civic Education and Leadership, National Taiwan Normal University, No.162, Section 1, Heping East Road, Da-An District, Taipei 106, Taiwan

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A B S T R A C T

In this paper, we extend the Taylor rule model of exchange rate determination by incorporating the liquidity yield on government bonds, and investigate exchange rate predictability from the augmented Taylor rule model. We find that the liquidity yield on government bonds delivers additional predictive power to future exchange rate movements beyond the model with Taylor rule fundamentals, using both in-sample and out-of-sample tests. In particular, the augmented model with liquidity yield exhibits superior predictive power after the currency swap market frictions are controlled.

1. Introduction

The seminal work by Meese and Rogoff (1983) shows that economic models of the exchange rate have difficulty outperforming a simple random walk model in terms of out-of-sample forecasts, even using *ex post* data on economic fundamentals. This apparently weak link between the nominal exchange rate and economic fundamentals has been subsequently explored and described, and is now well known as the "Meese–Rogoff puzzle" (Obstfeld and Rogoff, 2001). Although some recent studies have found that fundamentals-based exchange rate models perform well in predicting the exchange rate (see, e.g., Mark and Sul, 2001; Molodtsova and Papell, 2009; Molodtsova et al., 2008; Cerra and Saxena, 2010), the issue as to whether the fundamentals-based model predicts the exchange rate has thus far not led to consistent conclusions among macroeconomists (see Cheung et al., 2005; Rossi, 2013).

In a recent paper, Engel and Wu (2022) find that the liquidity yield on government bonds is essential in exchange rate determination. They derive the empirical specification of the exchange rate movement using a theoretical general equilibrium model extended from Engel (2016). In particular, their specification includes a measure of the liquidity yield on government bonds proposed by Du et al. (2018a). They find the changes in the liquidity yield explain exchange rate movements significantly. The liquidity yield in Engel and Wu (2022), which is referred to as the convenience yield, is defined as the nonpecuniary return provided because of the government bonds' safety, the ease with which they can be sold, and their value as collateral (Krishnamurthy and Vissing-Jorgensen, 2012; Jiang et al., 2018). Several studies have shown that the convenience yield plays a role in explaining the exchange rate puzzle. For instance, Engel (2016) extends the model à *la* Nagel (2016) and finds the model can explain why the high interest rate currency has the higher risk premium in the short run but pays a negative premium in the long run. Valchev (forthcoming) also studied a model

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* Corresponding author.
E-mail addresses: sschen@ntu.edu.tw (S.-S. Chen), yhchou@ntnu.edu.tw (Y.-H. Chou).
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in which the convenience yield plays a role in accounting for this puzzle, through the interaction between monetary and fiscal policies. Furthermore, Engel et al. (2019) extend the theoretical model of Engel (2016) to explain the empirical finding that the inflation rate predicts changes in the exchange rate better than the interest rate.

The intuition for why the government bond convenience yield influences the exchange rate is straightforward. The safety and liquidity that these bonds provide are attractive to investors, and influence their investment decisions. As for safety, government bonds can pay a lower pecuniary return than other bonds with similar risk characteristics, and still be desirable. Moreover, an increase in the liquidity yield, as measured by the difference between the private bond return and government bond return, will lead to a currency appreciation in much the same way that an increase in the interest rate would affect the currency value.

Engel and Wu (2022) demonstrate that the government liquidity yield is a significant determinant of exchange rate movements. In an exercise in the spirit of Meese and Rogoff (1983), they find their empirical model has a significantly better out-of-sample fit than a random walk model. However, it is crucial to note that in Engel and Wu (2022), the out-of-sample fit exercise of their empirical model is not exactly an out-of-sample forecast exercise because the contemporary (realized) value of the fundamental is used.[2] In reality, the realized values of economic fundamentals are not readily available when predicting future exchange rates. Therefore, while the empirical evidence in Engel and Wu (2022) establishes an important link between liquidity yield on government bonds and exchange rates, it is still not clear whether liquidity yield is truly useful and informative for forecasting purposes. We thus close this gap by considering a standard predictability test to investigate whether liquidity yields have one-period-ahead predictive power of future exchange rates, and further compare their predictive power with other models used in previous exchange rate forecasting studies.

Our empirical model is motivated by two key elements. The first building block is a simple model of exchange rate determination, which explicitly considers whether the *ex ante* excess return on short-term government bonds in one country relative to that in another is attributable to the liquidity premium, following Jiang et al. (2018) and Engel and Wu (2022). The second is the Taylor rule specifying that the central banks adjust the short-run nominal interest rate in response to inflation and the output gap for both countries. We then use the predictive regression implied by the model to evaluate exchange rate predictability, using both in-sample and out-of-sample tests.

We collected monthly data from 1997M1 to 2018M12 for G10 currencies (Australia, Canada, Denmark, the Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, and the UK, with the US serving as the numeraire), and followed Du et al. (2018a) and Engel and Wu (2022) to consider two measures of the relative liquidity yield on government bonds. The first is a relative measure of the spread between the yield on marketable securities and government bond yields in the home and foreign countries, while the second explicitly decomposes the first measure into a component that captures the frictions of the swap markets for foreign exchange, and a country-specific government bond liquidity yield component.

We find that, when controlling the foreign exchange swap market frictions, the model with liquidity yields has both in-sample and out-of-sample predictive power for the one-month-ahead exchange rate changes for seven out of 10 currencies. The in-sample tests are based on the significance of the coefficient from a one-month-ahead predictive regression model, while the out-of-sample forecasting performance is evaluated using the Clark–West (CW) test proposed by Clark and West (2006, 2007), which considers that under the null, the sample mean squared prediction errors (MSPEs) of the alternative model are expected to be greater than those of the random walk model. Hence, the proposed test adjusts for the upward shift in the sample MSPEs of the alternative model. Moreover, because 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 forecasters, we implement the test statistics proposed by Rossi and Inoue (2012), which are robust to data mining across different window sizes. The predictive ability of our model remains strongly significant using the Rossi and Inoue (2012) tests.

We then compare the predictive power of our model with the exchange rate models based on the Taylor rule fundamentals used in Molodtsova and Papell (2009). This exercise is particularly appealing because our model nests the empirical specification of Molodtsova and Papell (2009), which includes inflation, output gap, and lagged interest rate as regressors. In other words, our empirical specification uses the Taylor rule fundamentals augmented by liquidity yields. We find our model has a better in-sample goodness-of-fit, and the out-of-sample test statistics indicate our model has superior predictive power for one-month-ahead exchange rate changes. This suggests the liquidity yield on government bonds delivers information beyond the Taylor rule fundamentals in predicting exchange rate movements in the short run.[3] In addition, we also find the predictability of the liquidity yield remains when using alternative specifications of Taylor rule fundamentals, or controlling other fundamentals (interest rate fundamentals and monetary fundamentals), or using the non-US-related exchange rates, for the same currencies and time periods. This suggests that the liquidity yield on government bonds indeed improves short-run exchange rate predictability.

Overall, we examine the predictive ability of the liquidity yield for future exchange rate movements, and the results are robust to alternative specifications of fundamentals, and alternative measures of liquidity yield. That is, liquidity yields are of practical use for exchange rate forecasts.

At first glance, there appears to be a close relationship between some of the empirical results in Engel and Wu (2022) and those in this paper. However, our investigation differs from Engel and Wu (2022) in several ways. First, the empirical specification of Engel and Wu (2022), which includes liquidity yields, interest rates, and real exchange rates as explanatory variables, is derived from a New

[2] In Meese and Rogoff (1983), they demonstrate that even using realized values of the regressors, traditional fundamentals such as interest rates and monetary aggregates would have no out-of-sample predictive power for exchange rates.

[3] We also investigate the long-horizon predictability based on the model with liquidity yields in Section 6. However, the in-sample and out-of-sample test results are not pronounced.

Keynesian open economy general equilibrium model. Engel and Wu (2022) aim to demonstrate that the inclusion of the liquidity variable increases the explanatory power of the exchange rate model. However, this paper has a different goal. As motivated by Engel and Wu (2022), we examine whether the predictive performance of a prominent predictive model of exchange rates, the Taylor rule model proposed by Molodtsova and Papell (2009), can be further improved by augmenting the liquidity variable. As many studies have documented that the model with Taylor rule fundamentals exhibits superior predictive power than models with other fundamentals (Rossi, 2013; Molodtsova and Papell, 2009; Molodtsova et al., 2008; Molodtsova and Papell, 2013; Engel et al., 2007; Wu and Wang, 2012, among others), we examine whether the liquidity yields can deliver additional predictive content beyond the Taylor rule fundamentals in predicting exchange rate changes. That is, our predictive model includes inflation and output gap, which have been shown to be useful predictors of future exchange rate changes (Engel et al., 2019; Menkhoff et al., 2017; Colacito et al., 2020).

Second, as noted, our specification enables us to conduct the standard out-of-sample predictability test, while Engel and Wu (2022) conduct an out-of-sample fit exercise rather than an out-of-sample forecasting test because they include the contemporaneous changes of liquidity yields and interest rates as explanatory variables. Unlike the out-of-sample fitting results in Engel and Wu (2022), our out-of-sample forecasting results do not show much evidence of exchange rate predictability based on the test proposed by Clark and West (2006, 2007). However, we find there is much more evidence of exchange rate predictability when using the rolling supremum test proposed by Rossi and Inoue (2012), which is deemed to be robust to data mining over different window sizes, and is not considered in Engel and Wu (2022).

Third, in addition to the Taylor rule fundamentals, we show that because the liquidity yields can partly capture deviations from the uncovered interest parity (UIP) condition, it is easy to introduce the liquidity yields into other existing exchange rate models, such as the models with interest rate fundamentals and monetary fundamentals. We also find evidence that by augmenting these fundamentals with liquidity yields, the models generate better forecasts via in-sample and out-of-sample tests.

The remainder of the paper is organized as follows. Section 2 presents the empirical framework, and Section 3 describes the data. Section 4 presents the empirical results. Section 5 conducts robustness checks of the baseline results. Section 6 presents the results of the long-horizon predictability tests. Section 7 concludes.

2. Empirical models

Our empirical model is a simple extension of the model with Taylor rule fundamentals proposed by Molodtsova and Papell (2009), where we replace the UIP condition with a pricing equation incorporating the liquidity yield as proposed by Jiang et al. (2018).

As in Jiang et al. (2018), the expected one-period excess return on foreign government bonds (relative to domestic government bonds) is determined by the liquidity yield of domestic government bonds relative to foreign government bonds as follows:

$$i_t^* + \mathrm{E}_t s_{t+1} - s_t - i_t = \eta_t, \tag{1}$$

where i_t and i_t^* are the interest rates of domestic government bonds and foreign government bonds, respectively. s_t is defined as the log of the exchange rate (expressed as the domestic currency price of the foreign currency). Finally, η_t is defined as the liquidity return on home government bonds relative to foreign government bonds. Eq. (1) indicates that the expected one-period excess return on foreign government bonds relative to domestic bonds is determined by the liquidity yield of domestic government bonds relative to foreign government bonds. The foreign government bonds pay a higher expected pecuniary return if the domestic government bonds are more liquid (η_t increases). Rewriting (1) as $\mathrm{E}_t s_{t+1} - s_t = (i_t - i_t^*) + \eta_t$, we find that the home currency is expected to depreciate ($\mathrm{E}_t s_{t+1} - s_t$ rises) in response to an increase in η_t.

Engel (2016) provides a theoretical foundation for η_t using a two-country model. Specifically, η_t is expressed as:

$$\eta_t = \alpha\left(i_t - i_t^*\right) + \nu_t,\ \alpha > 0, \tag{2}$$

where ν_t is a mean-zero, independent and identically distributed random shock to the liquidity return, and α is a measure of the sensitivity of the excess return on foreign government bonds over domestic bonds. This equation suggests that the liquidity return of domestic government bonds is positively correlated with $i_t - i_t^*$. Engel (2016) shows that when the domestic interest rate is relatively high, the liquidity return of domestic government bonds will be relatively high as well. This is because the domestic interest rate increases under a contractionary monetary policy shock (which is assumed to be uncorrelated with ν_t), and therefore the representative agents in the model will value domestic government bonds more for their liquidity because the money supply has decreased.

To close the model, we assume that the Taylor rules of the monetary authority of the domestic country and the foreign country take the following forms:

$$i_t = \phi_0 + (1 - \phi_i)(\phi_\pi \pi_t + \phi_x x_t) + \phi_i i_{t-1}, \tag{3}$$

$$i_t^* = \phi_0^* + \left(1 - \phi_i^*\right)\left(\phi_\pi^* \pi_t^* + \phi_x^* x_t^*\right) + \phi_i^* i_{t-1}, \tag{4}$$

where π_t and x_t represent the inflation and output gap of the home country, respectively. ϕ_π, ϕ_x, and ϕ_i represent policy parameters that measure the response of the interest rate to inflation, output gap, and a one-period lag of the interest rate, respectively. The coefficient ϕ_0 is a constant that combines the long-run target of the interest rate and inflation rate of the home country, as in Molodtsova and Papell (2009); Molodtsova et al. (2008), among others. Asterisks denote foreign variables. It is worth noting that the Taylor rules in (3) and (4) are called Taylor rules with interest-rate smoothing because they include the lagged interest rate to allow for the possibility that the interest rate adjusts gradually to achieve its target level.

Subtracting Eq. (4) from Eq. (3) and using Eq. (1) to substitute for $i_t - i_t^*$, we obtain the predictive regression as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}, \quad (5)$$

where $\Delta s_{t+1} = s_{t+1} - s_t$, and $\theta_0, \cdots, \theta_7$ are the regression coefficients. Eq. (5) is the baseline specification of the empirical analysis in this paper. If we link the signs and magnitudes with Eqs. (3), (4), and (1), we have $\theta_0 = \phi_0 - \phi_0^*, \theta_1 = (1-\phi_i)\phi_\pi, \theta_2 = -(1-\phi_i^*)\phi_\pi^*, \theta_3 = (1-\phi_i)\phi_x, \theta_4 = -(1-\phi_i^*)\phi_x^*, \theta_5 = \phi_i, \theta_6 = -\phi_i^*$, and $\theta_7 = 1$. That is, according to Eq. (5), we would expect $\theta_1 > 0$ and $\theta_2 < 0$ if we impose the restrictions $\phi_\pi > 0$ and $\phi_\pi^* > 0$. However, Molodtsova and Papell (2009) and Engel et al. (2019) find that the signs of the estimated coefficients tend to be the opposite of those implied by interest parity and the Taylor rule, especially for the coefficients on domestic inflation and foreign inflation (US inflation). They argue that the reversal of signs appears to be consistent with the empirical findings of the UIP puzzle. Because the purpose of this paper is to examine exchange rate predictability based on the predictive regression (5), rather than the link between the predictive regression and the Taylor rules, in the empirical exercise, we do not impose restrictions on the signs and magnitudes of the estimated coefficients for any of the empirical models.

The explanatory variables in Eq. (5) include inflation, output gap, lagged interest rate, and relative liquidity yield of home government bonds of the home and foreign countries. This can be interpreted as an augmenting "heterogeneous and symmetric" Taylor rule model with interest-rate smoothing as used in Molodtsova and Papell (2009) and Engel et al. (2019) with the relative liquidity yield of home government bonds as an extra predictive variable.[4] In other words, Eq. (5) nests the "heterogeneous and symmetric" Taylor rule model in Molodtsova and Papell (2009) if we set $\theta_7 = 0$. Furthermore, it is worth noting that the specification "heterogeneous and symmetric" with interest-rate smoothing is the best specification in terms of forecasting performance among many variants of the Taylor rule considered in Molodtsova and Papell (2009). Thus, the empirical specification (5) enables us to investigate whether the relative liquidity yield of home government bonds can deliver additional predictive power of future exchange rates beyond the conventional Taylor rule fundamentals used in Molodtsova and Papell (2009) and Engel et al. (2019).

However, it is difficult to obtain reliable estimates of the unobserved shock, ν_t in Eq. (2). It may seem logical that if we regress η_t on $i_t - i_t^*$, we would obtain the estimated residuals as a proxy of ν_t. However, the problem of endogeneity will generate biased estimates of ν_t because in the model of Engel (2016), $i_t - i_t^*$ is an endogenous variable, and it responds to liquidity shocks, ν_t, therefore $i_t - i_t^*$ and ν_t are correlated. Thus, we follow Engel and Wu (2022) in using η_t as the measure of liquidity yield, and construct the benchmark measure of η_t as follows:

$$\eta_t \equiv \left(i_t^m - i_t\right) - \left(i_t^{m*} - i_t^*\right) = \left(i_t^m - i_t^{m*}\right) - \left(i_t - i_t^*\right),$$

where i_t^m and i_t^{m*} denote the return on short-term, one-period market securities of the home and foreign countries, and $i_t^m - i_t$ and $i_t^{m*} - i_t^*$ are liquidity yields in the home and foreign countries. Hence, by definition η_t is a relative measure of the difference between market securities and government bond yields in the home and foreign countries.

Alternatively, we also follow Engel and Wu (2022) to assume that the term $i_t^m - i_t^{m*}$ can be measured by $f_{t,t+1} - s_t$, where $f_{t,t+1}$ denotes the log of the forward rate at t for delivery at $t+1$, and s_t is the log of the spot exchange rate, both expressed in home currency price in a foreign currency. Hence, the relative liquidity yield η_t can be rewritten as:

$$\eta_t = \left(f_{t,t+1} - s_t + i_t^*\right) - i_t. \quad (6)$$

That is, the first three terms are the payoff of a synthetic home government bond that is constructed by buying the foreign government bond, and eliminating exchange rate risk in the spot market using a forward contract. Because the home government bond and the synthetic home government bond pay equivalent monetary returns, the difference between the two gives a measure of the relative difference in liquidity services provided by the home and foreign government bonds.

Finally, to consider the role of currency derivative market frictions in predicting exchange rate movements, we further follow Engel and Wu (2022) to decompose the relative liquidity yield. To do so, first we define $\tau_t \equiv f_{t,t+1} - s_t + RET_t^{IRS*} - RET_t^{IRS}$ to capture the deviation from covered interest parity (CIP) for market returns, where RET_t^{IRS} and RET_t^{IRS*} refer to the home and foreign returns on LIBOR swaps, respectively, and are used to proxy i_t^m and i_t^{m*}. Baba et al. (2008) and Baba and Packer (2009) attribute the failure of covered interest arbitrage in the years immediately following the global financial crisis to a liquidity factor. In particular, there appeared to be profitable arbitrage opportunities that involved borrowing in dollars and making covered investments in foreign interest-earning assets. These papers provide evidence that investors were reluctant to take advantage of such opportunities because there was a demand for liquidity in dollar assets. Du et al. (2018b) find that, even many years after the global financial crisis, the need for liquidity has fallen and the deviations from CIP remain; however, financial institutions are still not undertaking the arbitrage that would result in riskless profits. A possible explanation is that to take this arbitrage opportunity, banks need to borrow dollars and then invest them in foreign assets; but such an arbitrage investment, while risk free, requires a bank to increase its liabilities and assets, which may put it in violation of regulatory constraints.

[4] The term "heterogeneous" means the coefficients in the Taylor rules of the home and foreign countries are not assumed to be equal, and "symmetric" means the Taylor rules use the same variables in the home and foreign countries.

For these reasons, we decompose η_t to investigate the role of τ_t as follows:

$$\eta_t = \tau_t + \gamma_t - \gamma_t^*, \tag{7}$$

where $\gamma_t = RET_t^{IRS} - i_t$ and $\gamma_t^* = RET_t^{IRS*} - i_t^*$ denote the home and foreign liquidity yields on government bonds, respectively. Substituting (7) into Eq. (1), and using (3) and (4), we obtain:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* + \text{regression errors.} \tag{8}$$

According to Eq. (8), we are able to investigate the role of foreign exchange swap market frictions τ_t, and the country-specific government liquidity measures γ_t and γ_t^* in predicting the exchange rates. If we expect that the demand for the liquidity of home and foreign government bonds is essential in predicting exchange rate movements, we would expect that θ_8 and θ_9 are statistically significant. In sum, Eqs. (5) and (8) will be the benchmark empirical models to examine exchange rate predictability through in-sample and out-of-sample forecasting exercises.

It is worth noting that as discussed in Du et al. (2018b) and Engel and Wu (2022), the default risk of sovereign bonds can also affect the relative liquidity yield η_t. They use the credit default swap (CDS) premium quote as the measure of the expected loss associated with sovereign default risk. However, the CDS premium quote data for a one-year tenor or above in the IHS Markit database are only available after 2007 for many countries and are subject to a large number of missing observations at a monthly frequency. Because of data limitations, we ignore the possible sovereign default risk factors when constructing the relative liquidity yield measure for each country in this paper.[5]

3. Data

We analyze spot exchange rates and forward rates for Australia, Canada, Denmark, the Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, and the UK. We select the US as the numeraire, i.e., the foreign country. The end-of-month monthly data, typically from 1997M1 to 2018M12, are obtained from Thomson Reuters Datastream. The industrial production index is used as a proxy of real output, while the price level is measured by the consumer price index (CPI), both of which are obtained from International Financial Statistics (IFS) published by the International Monetary Fund. The inflation rate is constructed as the annual change (12-month difference) in the log of the consumer price. Because the industrial production series for Australia, New Zealand, and Switzerland, and the CPI series for Australia and New Zealand are only available quarterly, we transform these into a monthly frequency by cubic interpolation.[6] Finally, the benchmark measures the output gap as the deviation of actual output from a Hodrick–-Prescott (HP) trend. That is, allowing y_t and y_t^{HP} to denote the actual output and the HP trend obtained by the HP filter, the output gap of the home country and the foreign country is thus defined as $x_t = y_t - y_t^{HP}$ and $x_t^* = y_t^* - y_t^{HP*}$.

We follow Engel and Wu (2022) by using one-year forward rates and one-year government yields to construct the relative liquidity yields. Finally, the government bond yield data and LIBOR swap rates are obtained from Bloomberg. We collect the data from Bloomberg and Thomson Reuters using the tickers provided by Engel and Wu (2022) and Du et al. (2018a). We plot the liquidity yield η_t in Fig. 1. For the sake of comparison, we then plot the η_t against the foreign exchange swap market frictions τ_t, and the country-specific liquidity of government bonds γ_t and γ_t^* in Fig. 2.

4. Empirical results

4.1. In-sample results

Table 1 reports the coefficient estimates with Newey–West corrected t-statistics in parentheses, and the adjusted R^2 for Eq. (5).[7] First, we find θ_1 is generally insignificant except for Canada, the Euro Area and Norway, which suggests that the domestic inflation rate may not help explain exchange rate movements. Conversely, it shows that there is more evidence of the predictability of US inflation for future exchange rate movements because θ_2 are positive and significant for Australia, the Euro Area, New Zealand, Japan, Sweden, Switzerland, and the UK. This is consistent with the findings in Engel et al. (2019) that the US inflation rate is a much stronger predictor of future exchange rate changes than inflation rates in other countries.[8] Second, we find that θ_3 and θ_4 are almost insignificant for all the countries we considered, which suggests that the output gap, both for the home country and the US, does not have in-sample

[5] Du et al. (2018a) argue that for developed markets, sovereign default risks are negligible. Thus, η_t is mainly driven by the relative liquidity of between home and foreign government bonds.

[6] We follow convention and treat the nominal exchange rate as a nonstationary random variable, that is, s_t is I(1) and $s_{t+1} - s_t$ is I(0). Moreover, we follow Molodtsova and Papell (2009) and Engel and Wu (2022) to treat inflation, output gap, interest rates, and relative liquidity yields as stationary random variables.

[7] A Bartlett kernel with a Newey and West (1994) automatic bandwidth is used for the Newey–West estimator, and we do not report the estimates of the constant θ_0 for the sake of brevity.

[8] This can be attributed to the dominance of US monetary policy in determining the exchange rates, as discussed in Rey (2013) that the US might be able to follow a Taylor rule to set the interest rate in response to inflation, but other countries are constrained in their interest rate setting because they may need to adjust their interest rates in response to changes in the US interest rate. See the discussions in Engel et al. (2019).

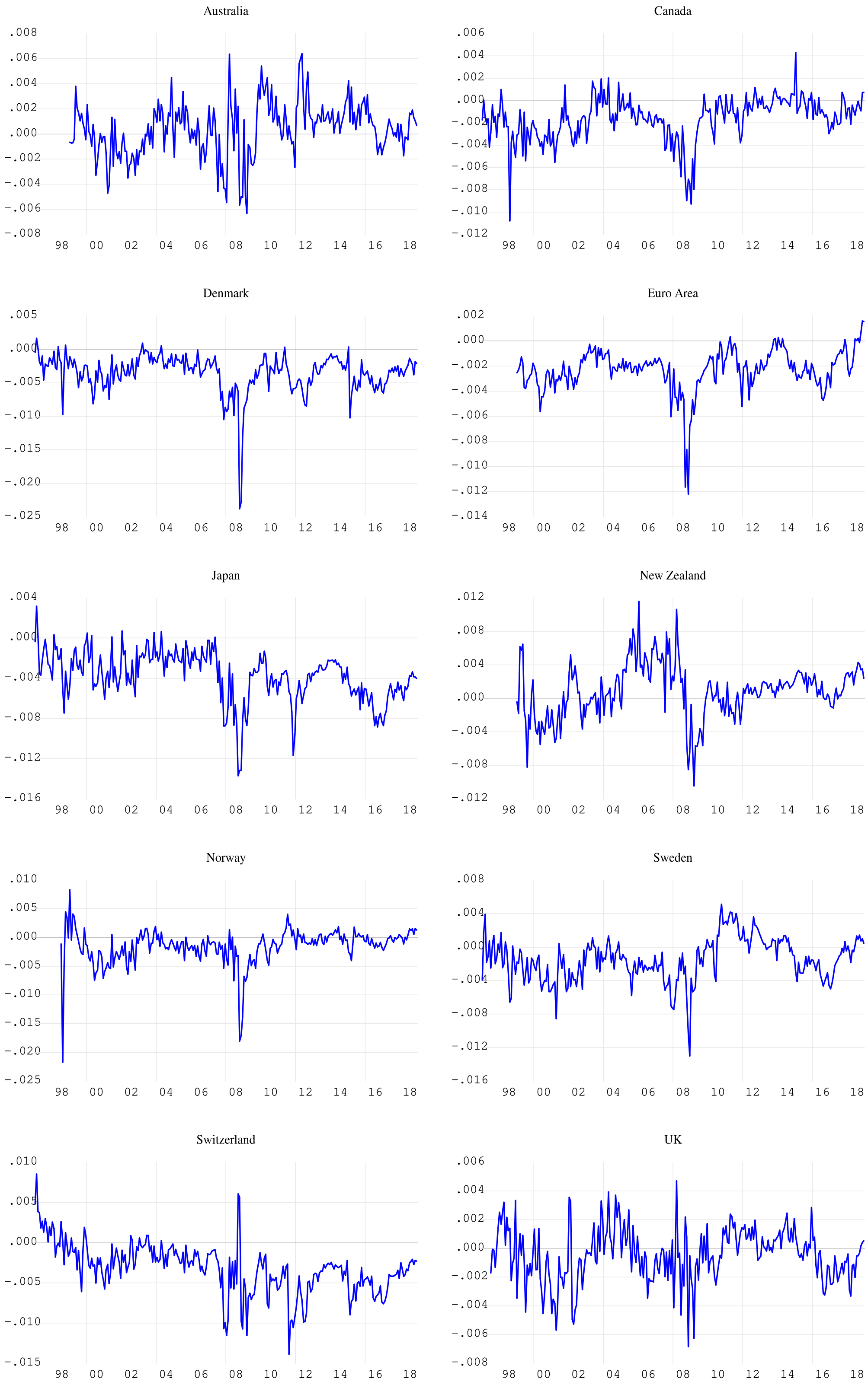

Fig. 1. Plots of the relative liquidity yield η_t.

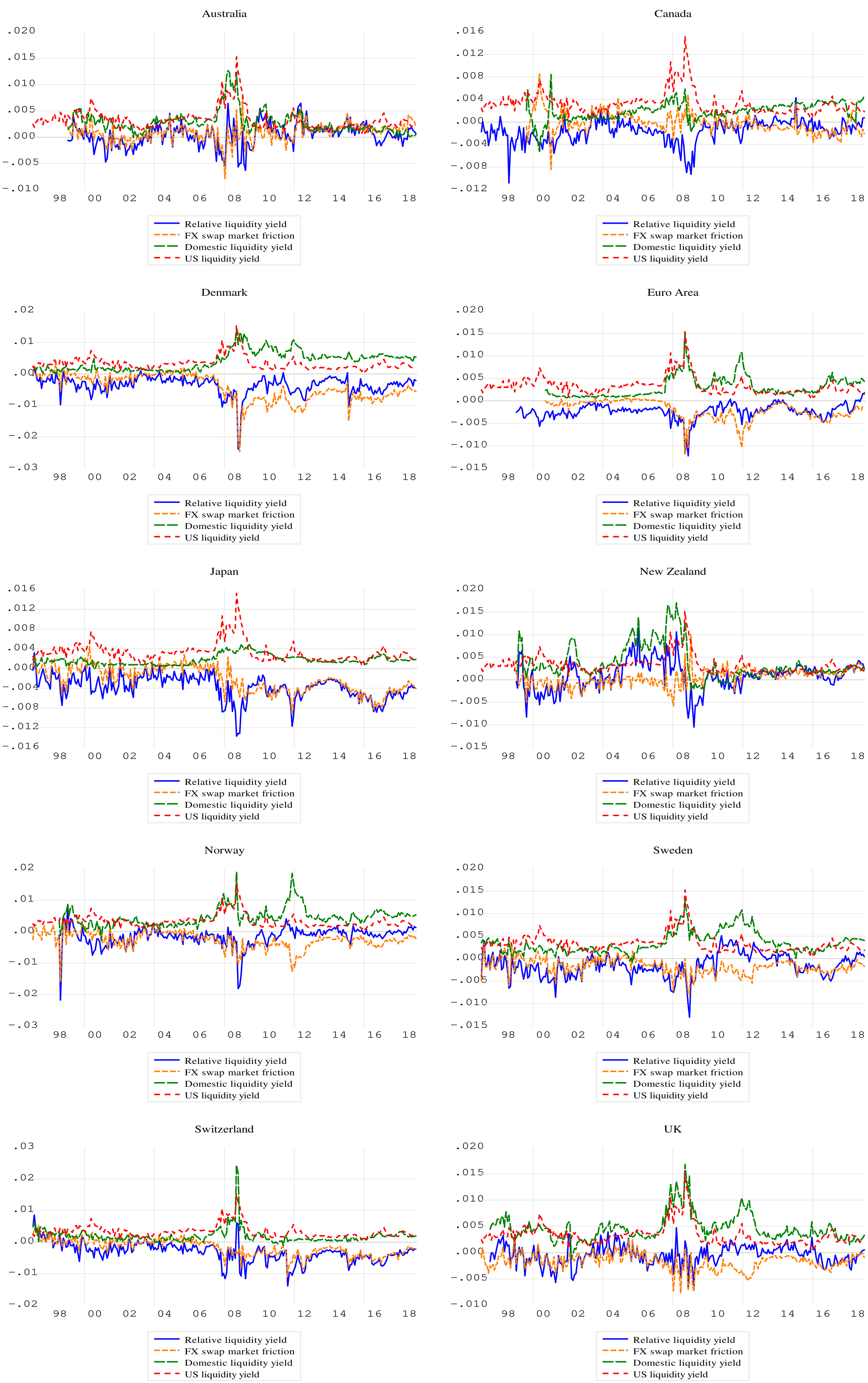

Fig. 2. Plots of the relative liquidity yield η_t, together with Foreign Exchange Market Frictions τ_t, and the measures of country-specific liquidity of government bonds γ_t and γ_t^*.

Table 1
In-sample predictability of liquidity yield: Estimation results of (5).

In-sample results								
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	$\overline{R}^2$
Australia	0.312	0.733**	0.359**	-0.025	-0.513***	0.112	2.181**	0.067
(1999M2–2018M7)	(1.488)	(2.010)	(2.141)	(-0.135)	(-3.017)	(0.809)	(2.195)	
Canada	-0.548**	0.358	0.156	0.002	0.060	-0.086	0.953	0.018
(1997M1–2018M12)	(-2.370)	(1.392)	(1.083)	(0.010)	(0.255)	(-0.436)	(0.842)	
Denmark	0.168	0.324	-0.038	0.013	-0.169	0.048	1.054	0.005
(1997M1–2018M12)	(0.536)	(1.335)	(-0.663)	(0.086)	(-0.975)	(0.316)	(1.334)	
Euro Area	-1.505***	1.518***	-0.131	0.068	0.276	-0.514***	-1.400	0.085
(2000M1–2018M4)	(-3.876)	(4.914)	(-1.051)	(0.381)	(1.359)	(-2.800)	(-1.110)	
Japan	0.281	0.253*	-0.113	0.125	-0.056	-0.209	3.696***	0.057
(1997M1–2018M8)	(1.515)	(1.927)	(-1.426)	(0.754)	(-0.072)	(-1.426)	(3.229)	
New Zealand	-0.342	0.710*	-0.053	0.215	-0.125	-0.022	-0.370	0.022
(1999M1–2017M10)	(-1.349)	(1.750)	(-0.325)	(1.256)	(-0.416)	(-0.088)	(-0.470)	
Norway	0.657***	0.426	0.087	0.066	-0.039	-0.129	1.511**	0.070
(1998M8–2018M8)	(2.853)	(1.586)	(1.178)	(0.050)	(-0.324)	(-0.803)	(2.097)	
Sweden	-0.298	0.780***	-0.154*	0.182	-0.057	-0.068	0.122	0.038
(1997M1–2018M12)	(-1.471)	(2.640)	(-1.819)	(0.968)	(-0.374)	(-0.420)	(0.131)	
Switzerland	-0.451	0.606**	0.014	-0.061	-0.406*	0.143	0.616	0.003
(1997M1–2017M10)	(-1.392)	(2.357)	(0.295)	(-0.504)	(-1.786)	(0.835)	(0.595)	
UK	-0.135	0.457***	0.042	-0.050	-0.174	0.114	2.369***	0.026
(1997M8–2018M12)	(-0.338)	(2.914)	(0.317)	(-0.423)	(-0.964)	(0.589)	(3.256)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

predictive power for the exchange rate. Third, the estimates of θ_5 are negative for eight of the 10 currencies, and insignificantly different from zero except for Australia and Switzerland. Furthermore, θ_6 is insignificant in nine out of the 10 countries we considered. This indicates the lagged interest rates, i_{t-1} and i_{t-1}^*, are not useful in predicting future exchange rate changes, which is again consistent with the argument in Engel et al. (2019) that the predictive power of interest rates is less pronounced than the inflation rate. Finally, we find θ_7 is positive for all the countries we considered, but only statistically significant for Australia, Japan, Norway, and the UK.

The in-sample estimation results of Eq. (8) are reported in Table 2. We note that the estimates of θ_7 are positive and significant in seven out of the 10 countries we considered. This implies that an increase in τ_t leads to an expected depreciation of the home currency ($E_t s_{t+1} - s_t$ rises). According to Du et al. (2018b), this is possible when there exists an excess demand for the foreign country's assets and the forward contracts to hedge the spot market exchange rate risk, such that the financial intermediaries have to mark up the forward rate because providing these currency-hedging contracts is costly for financial intermediaries. This markup of the forward rate is thus accompanied by a subsequent appreciation of the foreign currency, which is driven by excess international demand. The coefficient estimates of θ_8 are all significant and positive in seven out of the 10 countries we considered, which indicates that an increase in government bond liquidity of the home country is associated with an expected depreciation of the home currency in general. Finally, the estimates of θ_9 are insignificant except for Japan, Sweden, and Switzerland, which suggests that the government bond liquidity of the foreign country (which is the US in our case) does not have in-sample predictive power for bilateral exchange rate changes. This result contrasts with the arguments of Baba et al. (2008) and Baba and Packer (2009) that the apparent deviations from CIP are attributed to the demand for US Treasury bonds because the investors value their safety. Conversely, the significance of θ_8 implies that the effect of the relative liquidity yields on future exchange rate movements is mainly driven by the liquidity yield of the home country.

To highlight the importance of τ_t, we also consider the predictive regression below which excludes τ_t:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\gamma_t + \theta_8\gamma_t^* + \text{regression errors.} \tag{9}$$

Note that if $\tau_t = 0, \eta_t = \gamma_t - \gamma_t^*$. Eq. (9) thus becomes an alternative specification of our predictive regression if there is no foreign exchange swap market frictions, that is, CIP holds in the short-term securities market, $f_t - s_t = RET_t^{IRS} - RET_t^{IRS*}$.

Table 3 reports the in-sample prediction results based on (9). Comparing these with Table 2, the predictive power of γ_t becomes much weaker because θ_7 is significant at the 10% level only in Denmark and Switzerland. The value of adjusted R^2 is also smaller than that reported in Table 2 except for the Euro Area. Such findings provide evidence that the deviation from CIP in the securities market, τ_t, is essential in predicting future exchange rate movements.

The in-sample forecast performance of Eq. (8) outperforms (5) in terms of adjusted R^2, although the improvement of the adjusted R^2 is less prominent. Furthermore, we note that τ_t and γ_t significantly predict Δs_{t+1} in Canada, Denmark, and Sweden, but η_t does not. This can be understood using a simple variance decomposition as in Engel and Wu (2022). First, because $\eta_t = \tau_t + \gamma_t - \gamma_t^*$ implies $\Delta\eta_t = \Delta\tau_t + \Delta\gamma_t - \Delta\gamma_t^*$, taking the variance of both sides, we have:

$$\mathrm{Var}(\Delta\eta_t) = \mathrm{Var}(\Delta\tau_t) + \mathrm{Var}(\Delta\gamma_t) + \mathrm{Var}(\Delta\gamma_t^*) + 2\times\mathrm{Cov}(\Delta\tau_t, \Delta\gamma_t) - 2\times\mathrm{Cov}(\Delta\tau_t, \Delta\gamma_t^*) - 2\times\mathrm{Cov}(\Delta\gamma_t, \Delta\gamma_t^*).$$

Table 2
In-sample predictability of liquidity yield: Estimation results of (8).

In-sample results										
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	$\overline{R}^2$
Australia	0.310*	0.670**	0.338**	-0.024	-0.540***	0.060	3.315*	2.224	0.318	0.079
(1999M2–2018M7)	(1.667)	(2.076)	(2.308)	(-0.139)	(-2.856)	(0.420)	(1.839)	(1.217)	(0.170)	
Canada	-0.038	0.033	0.159	-0.115	0.131	-0.194	5.396***	6.217***	0.262	0.116
(1999M8–2018M12)	(-0.152)	(0.138)	(1.368)	(-0.749)	(0.394)	(-0.748)	(3.961)	(3.555)	(0.263)	
Denmark	-0.057	0.287	-0.027	0.005	-0.130	0.167	2.832**	5.067***	-0.687	0.041
(1997M1–2018M12)	(-0.164)	(1.176)	(-0.505)	(0.036)	(-0.570)	(1.071)	(2.335)	(2.969)	(-0.357)	
Euro Area	-1.617***	1.462***	-0.075	-0.017	0.363	-0.553***	0.049	1.294	0.318	0.082
(2000M9–2018M4)	(-3.744)	(4.592)	(-0.492)	(-0.082)	(1.488)	(-2.817)	(0.015)	(0.440)	(0.190)	
Japan	0.300*	0.262*	-0.115	0.135	-0.354	-0.185	3.862***	5.077*	-3.892***	0.050
(1997M8–2018M8)	(1.727)	(2.085)	(-1.121)	(0.764)	(-0.281)	(-1.234)	(2.583)	(1.712)	(-3.950)	
New Zealand	-0.384**	0.648**	0.042	0.154	-0.197	0.025	1.781	-0.372	3.631*	0.048
(1999M1–2017M10)	(-2.083)	(2.076)	(0.313)	(0.935)	(-0.953)	(0.141)	(1.428)	(-0.460)	(1.937)	
Norway	0.569***	0.346	0.060	0.055	-0.060	-0.252	2.961***	1.593*	1.076	0.083
(1997M1–2018M8)	(3.043)	(1.562)	(0.782)	(0.335)	(-0.562)	(-1.397)	(2.936)	(1.845)	(0.619)	
Sweden	-0.684	0.331	-0.139*	0.266	-0.181	-0.019	4.390**	1.107	3.314*	0.059
(1997M1–2018M12)	(-1.432)	(0.613)	(-1.890)	(1.766)	(-1.324)	(-0.129)	(3.077)	(0.984)	(1.903)	
Switzerland	-0.639*	0.645***	-0.011	-0.049	-0.272	0.200	-0.513	2.423**	-1.356	0.012
(1997M1–2017M10)	(-1.812)	(2.764)	(-0.214)	(-0.424)	(-1.018)	(1.310)	(-0.375)	(2.035)	(-0.871)	
UK	-0.338	0.373***	0.044	-0.051	-0.322	0.092	4.851***	2.343**	1.743	0.087
(1997M8–2018M12)	(-1.358)	(2.091)	(0.317)	(-0.365)	(-2.196)	(0.513)	(3.779)	(2.257)	(1.256)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Table 3
In-sample predictability of liquidity yield: Estimation results excluding τ_t.

	In-sample results								
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	$\overline{R}^2$
Australia	0.167	0.724**	0.338**	-0.006	-0.676***	0.095	2.025	0.646	0.062
(1999M2–2018M7)	(0.797)	(2.212)	(2.101)	(-0.029)	-3.130	(0.621)	(0.955)	(0.282)	
Canada	-0.379	0.228	0.155	-0.031	0.204	-3.000	1.564	1.777	0.045
(1999M8–2018M12)	(-1.521)	(0.921)	(1.259)	(-0.200)	(0.596)	(-1.158)	(1.414)	(1.480)	
Denmark	-0.245	0.510**	-0.049	-0.016	0.002	0.217	2.399**	-1.367	0.012
(1997M1–2018M12)	(-0.739)	(2.200)	(-0.939)	(-0.105)	(0.008)	(1.451)	(1.956)	(-0.779)	
Euro Area	-1.618***	1.463***	-0.075	-0.017	0.363	-0.553***	1.252	0.324)	0.086
(2000M9–2018M4)	(-3.775)	(4.822)	(-0.533)	(-0.086)	(1.562)	(-2.864)	(0.793)	(0.190)	
Japan	0.221	0.377*	-0.123	0.100	0.857	-0.033	-0.161	-3.494***	0.013
(1997M1–2018M8)	(1.219)	(1.831)	(-1.449)	(0.613)	(0.821)	(-0.238)	(-0.067)	(-2.863)	
New Zealand	-0.410**	0.664**	0.021	0.170	-0.261	-0.014	-0.474	3.958*	0.047
(1999M1–2017M10)	(-2.148)	(2.089)	(0.151)	(0.963)	(-1.189)	(-0.071)	(-0.578)	(1.918)	
Norway	0.573***	0.434**	0.059	0.085	-0.104	-0.132	0.364	0.389	0.049
(1998M8–2018M8)	(2.810)	(1.866)	(0.734)	(0.509)	(-0.951)	(-0.824)	(0.446)	(0.269)	
Sweden	-0.430**	0.764***	-0.140*	0.171	-0.106	-0.120	-0.138	1.859	0.053
(1997M1–2018M12)	(-2.259)	(2.768)	(-1.727)	(0.914)	(-0.804)	(-0.751)	(-0.132)	(1.365)	
Switzerland	-0.680*	0.651***	-0.006	-0.046	-0.292	0.163	2.403**	-1.122	0.015
(1997M1–2017M10)	(-1.942)	(2.769)	(-0.118)	(-0.404)	(-1.113)	(1.314)	(2.020)	(-0.696)	
UK	-0.476**	0.480***	-0.008	-0.016	-0.221	0.036	0.933	1.625	0.029
(1997M8–2018M12)	(-2.063)	(2.759)	(-0.057)	(-0.110)	(-1.486)	(0.193)	(0.936)	(1.260)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\gamma_t + \theta_8\gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Dividing both sides by $\mathrm{Var}(\Delta\eta_t)$, we obtain:

$$1 = \frac{\mathrm{Var}(\Delta\tau_t)}{\mathrm{Var}(\Delta\eta_t)} + \frac{\mathrm{Var}(\Delta\gamma_t)}{\mathrm{Var}(\Delta\eta_t)} + \frac{\mathrm{Var}\left(\Delta\gamma_t^*\right)}{\mathrm{Var}(\Delta\eta_t)} + 2\times\frac{\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t)}{\mathrm{Var}(\Delta\eta_t)} - 2\times\frac{\mathrm{Cov}\left(\Delta\tau_t,\Delta\gamma_t^*\right)}{\mathrm{Var}(\Delta\eta_t)} - 2\times\frac{\mathrm{Cov}\left(\Delta\gamma_t,\Delta\gamma_t^*\right)}{\mathrm{Var}(\Delta\eta_t)}. \tag{10}$$

We report the variance decomposition results based on Eq. (10) in Table 4. We find the sums of the variance shares of $\Delta\tau_t$, $\Delta\gamma_t$, and $\Delta\gamma_t^*$ are greater than one for all countries we considered, which arises because $\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t^*)$, and $\mathrm{Cov}(\Delta\gamma_t,\Delta\gamma_t^*)$ are positive. We also find that $\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t)$ are negative in many countries (Canada, Denmark, the Euro Area, Japan, Norway and the UK), which can be justified when the LIBOR rate in the home country is considered risky, where RET_t^{IRS} increases, as well as the liquidity of the home government bond γ_t. Meanwhile, the excess return of the foreign country relative to the home country in money market instrument $f_t - s_t + RET_t^{IRS} - RET_t^{IRS*}$ falls because the foreign LIBOR is less risky, that is, τ_t falls. In particular, we find the share of $2\times\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t)$, $-2\times\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t^*)$ and $-2\times\mathrm{Cov}(\Delta\gamma_t,\Delta\gamma_t^*)$ contributes a large share of the variation in $\Delta\eta_t$ in many countries, and the contribution share of $\mathrm{Var}(\Delta\tau_t)$ is greater than one in Canada and Sweden. This implies that the variations in τ_t, γ_t, and γ_t^* are greatly offset when using η_t to predict the exchange rate movement of the exchange rates, such as the Canadian dollar and Swedish krona relative to the US dollar, therefore, η_t may fail to deliver information about future exchange rate movements.

Table 4
Variance decomposition of η_t.

	Variance decomposition of $\Delta\eta_t$					
Home Currency	$\frac{\mathrm{Var}(\Delta\tau_t)}{\mathrm{Var}(\Delta\eta_t)}$	$\frac{\mathrm{Var}(\Delta\gamma_t)}{\mathrm{Var}(\Delta\eta_t)}$	$\frac{\mathrm{Var}(\Delta\gamma_t^*)}{\mathrm{Var}(\Delta\eta_t)}$	$2\times\frac{\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t)}{\mathrm{Var}(\Delta\eta_t)}$	$-2\times\frac{\mathrm{Cov}(\Delta\tau_t,\Delta\gamma_t^*)}{\mathrm{Var}(\Delta\eta_t)}$	$-2\times\frac{\mathrm{Cov}(\Delta\gamma_t,\Delta\gamma_t^*)}{\mathrm{Var}(\Delta\eta_t)}$
Australia	0.997	0.241	0.257	0.081	−0.377	−0.197
Canada	1.308	0.515	0.486	-0.592	−0.493	-0.219
Denmark	0.890	0.179	0.202	−0.054	-0.112	−0.104
Euro Area	0.936	0.731	0.785	−1.225	0.710	−0.930
Japan	0.795	0.046	0.327	−0.026	-0.085	−0.056
New Zealand	0.681	0.436	0.176	0.027	−0.225	−0.094
Norway	0.679	0.459	0.153	−0.073	−0.054	−0.163
Sweden	1.997	0.252	0.311	0.326	−0.365	−0.148
Switzerland	1.034	0.645	0.184	0.389	−0.125	−0.226
UK	0.666	0.570	0.275	−0.002	−0.125	−0.312

Note: The numbers represent the share of each factor in explaining the variance of $\Delta\eta_t$.

Furthermore, to compare our empirical models with a standard model of Taylor rule fundamentals, we also estimate a predictive regression based on a "heterogeneous and symmetric" Taylor rule model in Molodtsova and Papell (2009) as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors.} \tag{11}$$

Table 5 reports the in-sample estimation result of Eq. (11). We find that the US inflation rate significantly predicts future exchange rate movements in Australia, the Euro Area, New Zealand, Norway, Sweden, Switzerland, and the UK. However, other predictors implied by the Taylor rule fundamentals, such as the inflation rate of the home country, output gap, and interest rates of home and foreign countries, are insignificant in general. Furthermore, it is evident that the $\overline{R}^2$ values in Table 5 are much smaller than those in Tables 1 and 2. Overall, although the results are not overwhelming, we find some evidence that the predictive regression solely based on the Taylor rule fundamentals may not well predict future exchange rate movements according to the in-sample predictive test results.

In sum, the in-sample analysis shows that we can obtain much more information about future exchange rate movements using the model with liquidity yields, as the predictive content of the liquidity yield remains when controlling for the predictors related to Taylor rule fundamentals.

4.2. Out-of-sample results

We follow Molodtsova and Papell (2009) and Engel et al. (2019) by employing rolling estimation to obtain out-of-sample forecasts. We concentrate on one-step-ahead forecasting to evaluate the out-of-sample forecast accuracy. Assume that the sample size is $T+1$, and $T+1 = R+P$, where the first R observations are used for estimation and P is equal to the number of forecasts. Information prior to t is used to forecast for periods $t = R, R+1, R+2, \cdots, T+1$. The first forecast period is $R+1$ and the final forecast period is $T+1$. We use the CW test proposed by Clark and West (2006, 2007) to test the null of no predictability against the alternative that the suggested model is more accurate than the driftless random walk model. Let $\mathscr{M}_1$ and $\mathscr{M}_2$ represent the random walk model and our baseline predictive regression model; we calculate the average of the one-step-ahead squared prediction errors for the out-of-sample period, and denote them as MSPE($\mathscr{M}_1$) and MSPE($\mathscr{M}_2$), respectively. The testing hypotheses are:

$$H_0 : \text{MSPE}(\mathscr{M}_1) = \text{MSPE}(\mathscr{M}_2),$$

$$H_a : \text{MSPE}(\mathscr{M}_1) > \text{MSPE}(\mathscr{M}_2).$$

To implement the CW test, first we let $\widehat{u}_{t+1}(\mathscr{M}_1)$ and $\widehat{u}_{t+1}(\mathscr{M}_2)$ be the forecasting errors for the random walk and baseline models, and $\widehat{\Delta s_{t+1}}(\mathscr{M}_1)$, $\widehat{\Delta s_{t+1}}(\mathscr{M}_2)$ the predicted one-period-ahead exchange rate changes of the random walk and baseline models, respectively. The CW test statistics can be constructed as follows:

Table 5
In-sample exchange rate predictability: Conventional Taylor rule model (11).

	In-sample results						
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	$\overline{R}^2$
Australia	0.156	0.810**	0.368*	0.222	-0.490***	0.034	0.057
(1999M2–2018M7)	(0.717)	(2.098)	(1.941)	(0.118)	(-2.633)	(0.216)	
Canada	-0.540**	0.346	0.136	0.035	0.009	-0.080	0.016
(1997M1–2018M12)	(-2.279)	(1.318)	(0.962)	(0.210)	(0.036)	(-0.415)	
Denmark	0.083	0.375	-0.054	0.001	-0.193	0.088	-0.000
(1997M1–2018M12)	(0.268)	(1.570)	(-0.945)	(0.010)	(-1.010)	(0.568)	
Euro Area	-1.473***	1.486***	-0.134	0.062	0.319	-0.518***	0.084
(2000M1–2018M4)	(-3.751)	(4.499)	(-1.071)	(0.340)	(1.407)	(-2.548)	
Japan	0.234	0.190	-0.101	0.097	-0.584	-0.012	-0.009
(1997M1–2018M8)	(1.189)	(1.051)	(-1.267)	(0.503)	(-0.670)	(-0.100)	
New Zealand	-0.324	0.699*	-0.056	0.201	-0.144	-0.009	0.026
(1999M1–2017M10)	(-1.242)	(1.707)	(-0.345)	(1.199)	(-0.486)	(-0.037)	
Norway	0.586***	0.468*	0.066	0.097	-0.095	-0.153	0.056
(1998M8–2018M8)	(2.620)	(1.763)	(0.889)	(0.628)	(-0.806)	(-1.030)	
Sweden	-0.305	0.787***	-0.153*	0.182	-0.058	-0.075	0.042
(1997M1–2018M12)	(-1.377)	(2.752)	(-1.800)	(0.972)	(-0.376)	(-0.537)	
Switzerland	-0.417	0.609**	0.007	-0.068	-0.434**	0.200	0.004
(1997M1–2017M10)	(-1.265)	(2.444)	(0.144)	(-0.544)	(-1.997)	(1.603)	
UK	-0.134	0.430***	0.021	0.008	-0.095	-0.017	0.004
(1997M8–2018M12)	(-0.379)	(2.834)	(0.156)	(0.065)	(-0.544)	(-0.091)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors}$. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

$$\mathrm{CW} = \frac{\sqrt{P}\bar{f}}{\sqrt{\widehat{V}}},$$

where $\bar{f} = P^{-1}\sum_{t=T-P+1}^{T}\widehat{f}_{t+1}$, $\widehat{f}_{t+1} = (\widehat{u}_{t+1}(\mathscr{M}_1))^2 - [\widehat{u}_{t+1}(\mathscr{M}_2)^2 - (\widehat{\Delta s_{t+1}}(\mathscr{M}_1) - \widehat{\Delta s_{t+1}}(\mathscr{M}_2)]$, and $\widehat{V}$ is the sample variance of $\widehat{f}_{t+1} - \bar{f}$.

As shown in Rossi and Inoue (2012), the out-of-sample forecasting results based on Clark and West (2006, 2007) may depend on the choice of the rolling window R. If the researcher uses a data mining procedure over different window sizes to generate the "best" out-of-sample forecasting results (i.e., the rolling window that generates the smallest MSPEs), then the tests based on the chosen rolling window may lead to serious size distortions. To overcome this problem, we follow Rossi and Inoue (2012) to consider a rolling supremum test following Clark and McCracken (2001), which is robust to the choice of the window size, as follows:[9]

$$\sup_{R\in[\underline{R},\ldots,\overline{R}]}\mathrm{ENCNEW}\left(\mathrm{R}\right), \tag{12}$$

where R denotes the window size, and $\underline{R} \equiv \mu T$ and $\overline{R} \equiv (1-\mu)T$ denote the smallest and the largest window sizes, respectively. $\mu \in [0, 1]$ is the ratio of the smallest window size relative to the sample size T. Furthermore,

$$\mathrm{ENCNEW(R)} = P\frac{P^{-1}\sum_{t=T-P+1}^{T}\left[(\Delta s_{t+1} - \widehat{\Delta s_{t+1}}(\mathscr{M}_1))^2 - \left(\Delta s_{t+1} - \widehat{\Delta s_{t+1}}\left(\mathscr{M}_1\right)\right)\left(\Delta s_{t+1} - \widehat{\Delta s_{t+1}}\left(\mathscr{M}_2\right)\right)\right]}{P^{-1}\sum_{t=T-P+1}^{T}(\Delta s_{t+1} - \widehat{\Delta s_{t+1}}(\mathscr{M}_2))^2}.$$

Rossi and Inoue (2012) apply the supremum-type ENCNEW test to investigate exchange rate predictability based on a model with Taylor rule fundamentals proposed by Molodtsova and Papell (2009). Compared with the results in Molodtsova and Papell (2009), their empirical evidence is much more favorable toward the model with the Taylor rule fundamentals in terms of predictive ability.

The out-of-sample forecasting results based on the CW test and sup-ENCNEW test are reported in Tables 6 and 7, respectively. We follow Molodtsova and Papell (2009) and Engel et al. (2019) to set $R = 120$ when calculating the CW statistics, and set $\mu = 0.15$ and calculate over window size $R \in [0.15T, 0.85T]$ to construct the sup-ENCNEW test statistics. For both tests, we compared the forecasting performance of the proposed models with the driftless random walk model and the random walk with a drift. It is clear that the predictive regression of (5), which includes η_t as a predictor, does not generally out-forecast the random walk because the CW statistics are insignificant for eight out of 10 currencies, except for Japan and the UK. Furthermore, the CW tests indicate that the empirical model (8) significantly outperforms the driftless random walk for three out of 10 countries (Canada, Japan, and Switzerland) at the 10% level. In sum, the CW tests indicate that the predictive regressions (5) and (8) do not have much out-of-sample predictive power for exchange rate changes. The fifth and sixth columns of Table 6 report the CW tests based on the model with the Taylor rule fundamentals in Molodtsova and Papell (2009). The empirical results may suggest that the standard Taylor rule model would not be significantly better than the random walk except for Norway, which suggests that the out-of-sample forecasting power of the model with the standard Taylor rule fundamentals is weak when using the most recent data.

Table 7 reports the out-of-sample test results based on the sup-ENCNEW test proposed by Rossi and Inoue (2012). The sup-ENCNEW statistics provide much stronger support for the predictive power of (5) and (8). For instance, the predictive model in Eq. (5) outperforms the random walk with a drift for seven out of 10 countries (Australia, Canada, the Euro Area, Japan, Norway, Sweden, and the UK), while the model in Eq. (8) outperforms the random walk with drift for six out of 10 countries (Canada, the Euro Area, Japan, Norway, Sweden, and the UK) at the 10% level. This result suggests the predictive regression with regressors related to liquidity yields and Taylor rule fundamentals can generate better forecasts than the random walk according to the tests of the nested models' forecasting comparison. The last two columns of Table 7 report the results based on the Taylor rule model of Molodtsova and Papell (2009). We find the predictive power of the Taylor rule model is weaker than Eqs. (5) and (8), but it still significantly outperforms the random walk (with and without drift) for Australia, Canada, the Euro Area, Norway, and Sweden at the 5% level. This result confirms the empirical findings in Rossi and Inoue (2012) that the empirical evidence in favor of exchange rate predictability is much stronger when allowing a wider search over window sizes.

However, we do not know whether the predictive regressions (5) and (8) outperform the predictive regression based solely on conventional Taylor rule fundamentals in (11) from Tables 6 and 7. To demonstrate that augmenting the Taylor rule model in (11) with η_t, τ_t, γ_t, and γ_t^* can enhance the predictive power, we implement the nested out-of-sample forecast comparison tests by setting $\mathscr{M}_1$ equal to Eq. (11), and $\mathscr{M}_2$ equal to Eq. (5) or (8). Table 8 reports the results based on the CW and sup-ENCNEW tests. According to the second column in Table 8, the CW tests suggest that Eq. (8) outperforms the conventional Taylor rule model (11) in four out of 10 countries. More evidence in favor of Eqs. (5) and (8) is found when using the sup-ENCNEW tests. The third and fourth columns in Table 8 indicate that Eqs. (5) and (8) outperform the Taylor rule model in six and seven out of 10 countries, respectively. This implies the baseline predictive models (5) and (8) do a better job in predicting change in future exchange rates than the conventional Taylor rule model (11).

[9] According to Clark and McCracken (2001), "ENCNEW" is the abbreviation for "a new encompassing test statistic."

Table 6
Out-of-sample predictability comparison of models with liquidity yields with random walk: CW tests.

Out-of-sample results						
Home Currency	Compare (5) with driftless RW	Compare (5) with RW with a drift	Compare (8) with driftless RW	Compare (8) with RW with a drift	Compare (11) with drftless RW	Compare (11) with RW with a drift
Australia	1.353*	1.051	0.717	0.188	1.398*	1.088
Canada	0.204	0.244	1.987**	2.121**	0.295	0.475
Denmark	-0.420	-0.414	-0.251	-0.197	0.286	0.411
Euro Area	-0.166	0.051	0.319	0.474	0.082	0.306
Japan	1.846**	1.862**	1.577*	1.527*	0.086	0.195
New Zealand	0.642	0.451	0.319	0.474	0.082	0.306
Norway	0.827	0.832	0.968	0.903	1.772*	1.741**
Sweden	0.961	0.899	1.205	1.112	1.177	1.116
Switzerland	0.351	0.207	0.400	0.337	-0.230	-0.387
UK	1.496*	1.697**	2.045**	2.024**	1.055	1.259

Note: The predictive regressions of (5), (8) and (11) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}$, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* + \text{regression errors}$ and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors}$, respectively. The critical values are 1.282 (10%), 1.645 (5%) and 2.326 (1%) respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

Table 7
Out-of-sample predictability comparison of models with liquidity yields with random walk: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results						
Home Currency	Compare (5) with driftless RW	Compare (5) with RW with a drift	Compare (8) with driftless RW	Compare (8) with RW with a drift	Compare (11) with driftless RW	Compare (11) with RW with a drift
k	8	7	10	9	7	6
Australia	13.777*	15.817**	7.067	8.662	12.465*	15.3111**
Canada	22.850***	24.623***	16.648**	18.257**	13.827**	15.477**
Denmark	0.294	0.610	3.813	1.028	2.589	3.221
Euro Area	12.426*	16.085*	11.630	14.173*	13.935**	18.339***
Japan	21.359***	24.420***	18.286**	21.197***	4.707	6.512
New Zealand	2.335	2.986	1.093	1.176	2.713	2.059
Norway	11.351*	14.181**	13.576*	16.196**	15.763**	18.529**
Sweden	17.909**	21.005***	22.986***	23.780***	23.019***	25.992***
Switzerland	3.498	2.661	4.688	5.660	1.371	1.059
UK	11.075	12.050*	17.505**	17.678**	6.553	7.802

Note: The predictive regression of (5), (8) and (11) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}$, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* + \text{regression errors}$ and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors}$, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the number of regressors in the small model (random walk). The critical values for 9.703 (10%), 12.030 (5%) and 17.132 (1%) for $k = 6$, 10.466(10%), 12.968(5%), and 18.406 (1%) for $k = 7$, 11.226 (10%), 13.831 (5%) and 19.489 (1%) for $k = 8$, 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, 12.502 (10%), 15.408 (5%), and 21.406 (1%) for $k = 10$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

Although the CW and sup-ENCNEW test statistics reported in Tables 6–8 indicate the model with liquidity yields appears to be a better model for exchange rate forecasting than the random walk or the conventional Taylor rule model, it does not mean the model with liquidity yields has a lower MSPE or root-mean-square error (RMSE) than the random walk or the Taylor rule model. As argued by Engel et al. (2019) and Clark and West (2007), nested out-of-sample forecast comparison tests, such as the CW test, compare the forecasting performance of a more general model, which has more parameters to estimate, with a nested model that has fewer parameters to estimate. In other words, even if the model with liquidity yields is true, one may do worse at predicting exchange rate changes because the estimated parameters may be subject to bias. To correct this problem, the CW test statistic incorporates a term to correct the RMSE of the more general model to take the estimation bias into account. That is, one may find the general model produces a better prediction than the random walk model according to the CW test, but the out-of-sample RMSE of the general model can be larger than the nested model.

With this caveat in mind, we calculate the ratio of the RMSE of the nested model (which can be either a random walk or the Taylor rule model) to the RMSE of our baseline predictive models, $\text{RMSE}(\mathscr{M}_1)/\text{RMSE}(\mathscr{M}_2)$. If $\text{RMSE}(\mathscr{M}_1)/\text{RMSE}(\mathscr{M}_2) > 1$, it implies the nested model has a higher RMSE, which suggests our predictive regressions perform better than the nested model. Table 9 reports the ratio of $\text{RMSE}(\mathscr{M}_1)/\text{RMSE}(\mathscr{M}_2)$ based on the CW and sup-ENCNEW tests, with $R(\text{CW})$ and $R(\text{sup}-\text{ENCNEW})$ denoting the rolling

Table 8
Out-of-sample comparison test: Compare with conventional Taylor rule model.

Home Country	CW test Compare (5) with (11)	Compare (8) with (11)	sup-ENCNEW test Compare (5) with (11)	Compare (8) with (11)
	$R = 120$	$R = 120$	$k = 1$	$k = 3$
Australia	0.639	−0.830	1.929	6.555
Canada	−0.257	3.782***	12.777***	27.114***
Denmark	−0.974	−0.277	4.341*	4.757
Euro Area	−2.251	−0.599	0.679	7.856*
Japan	2.306**	1.767**	27.270***	16.455***
New Zealand	-1.089	−0.847	0.096	4.970
Norway	−0.571	−0.841	8.262***	16.273***
Sweden	−0.816	1.438*	0.704	11.104**
Switzerland	0.397	0.587	4.701*	14.638***
UK	1.015	2.700***	13.392***	14.436***

Note: The predictive regressions of (5), (8) and (11) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t +$ regression errors, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* +$ regression errors and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* +$ regression errors, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the number of regressors in the small model (random walk). The critical values for the CW test are 1.282 (10%), 1.645 (5%) and 2.326 (1%). And the critical values for the sup-ENCNEW test are 3.938 (10%), 5.211 (5%) and 8.125 (1%) for $k = 1$ and 6.908(10%), 8.677(5%) and 12.615 (1%) for $k = 3$. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance levels, respectively.

window size corresponding to the CW and sup-ENCNEW tests, respectively.[10] The first to fourth columns of Table 9 report the ratio that compares the out-of-sample RMSE of the random walk to our baseline predictive models. We find the ratio is smaller than one in almost all cases, which is consistent with the empirical findings in Engel et al. (2019) and Rogoff and Stavrakeva (2008) that it is still difficult to beat the random walk model overwhelmingly when directly comparing with the RMSE between the random walk model and the competing model. However, we find some evidence that our baseline predictive regressions (5) and (8) generate smaller RMSE than the Taylor rule model (11). For example, the fifth column in Table 9 shows that the RMSE ratios are greater than one when we compare the Taylor rule model (11) with the predictive regression (5) in seven out of 10 countries. This further confirms that our benchmark predictive regressions (5) and (8) generate better predictions than the conventional Taylor rule model according to our out-of-sample forecasting exercise.

Overall, our empirical results show that the model with liquidity yields predicts future exchange rate movements well in the out-of-sample forecast exercise, and supports the conclusions drawn from the in-sample analysis. In particular, the model with liquidity yields significantly outperforms the conventional Taylor rule model.

It is worth noting that our out-of-sample forecasting exercise indicates the model with the liquidity yield cannot beat the random walk model in Denmark and Switzerland, which can be explained as follows. Because the Denmark krone is pegged to the euro, the fundamentals of Denmark may not be very informative about the future exchange rate movements. As for Switzerland, the Swiss National Bank set the peg to the euro in 2011 after the Eurozone crisis, but unexpectedly abandoned the peg of 1.20 francs per euro in January, 2015. The Swiss franc then exhibited dramatic appreciation in that month, and showed an appreciating trend against the euro in 2016–2018 despite the low Swiss interest rates. Because our sample period covers these events, it makes the prediction of the Swiss franc exchange rate very difficult.[11]

5. Robustness checks

In this section, we present several checks for robustness, including an alternative specification of the Taylor rule, an alternative measure of the output gap, an augmented monetary model incorporating liquidity yields, and alternative measures of the liquidity yield. We report the in-sample prediction result, and the out-of-sample predicting statistics based on Rossi and Inoue (2012).[12]

5.1. *Alternative specification of the Taylor Rule*

We also follow Molodtsova and Papell (2009) and Clarida et al. (1998) to consider a variant of the Taylor rule of the home country, which includes the real exchange rate in addition to inflation and the output gap as follows:

$$i_t = \phi_0 + (1-\phi_i)(\phi_\pi\pi_t + \phi_x x_t + \phi_q q_t) + \phi_i i_{t-1}, \tag{13}$$

[10] $R(\text{CW})$ is prespecified as $R = 120$, while $R(\sup-\text{ENCNEW})$ represents the window size corresponding to the sup-ENCNEW test statistics.
[11] Engel and Wu (2022) conduct an out-of-sample fit exercise and find that the MSPE for Switzerland is higher than the random walk.
[12] We do not report CW test results because they are typically weaker than the test results of Rossi and Inoue (2012).

Table 9
Out-of-sample RMSE: models with liquidity yields compared with random walks and conventional Taylor rule models. Window size is chosen by CW and sup-ENCNEW tests.

Out-of-sample results						
Home Currency	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$	$\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$
	$\mathcal{M}_1$: **Driftless RW** $\mathcal{M}_2$: (5)	$\mathcal{M}_1$: **RW with a drift** $\mathcal{M}_2$: (5)	$\mathcal{M}_1$: **Driftless RW** $\mathcal{M}_2$: (8)	$\mathcal{M}_1$: **RW with a drift** $\mathcal{M}_2$: (8)	$\mathcal{M}_1$: (11) $\mathcal{M}_2$: (5)	$\mathcal{M}_1$: (11) $\mathcal{M}_2$: (8)
Australia						
R(CW)	0.941	0.945	0.916	0.919	1.001*	0.974
R(sup-ENCNEW)	0.787	0.803	0.739	0.754	1.000*	0.971
Canada						
R(CW)	0.931	0.939	0.983	0.994	0.988	1.096*
R(sup-ENCNEW)	0.897	0.903	1.038*	1.045*	1.011*	1.116*
Denmark						
R(CW)	0.907	0.913	0.905	0.910	0.943	0.940
R(sup-ENCNEW)	0.964	0.971	0.976	0.987	0.979	1.018*
Euro Area						
R(CW)	0.926	0.936	0.904	0.914	0.989	0.966
R(sup-ENCNEW)	0.848	0.815	0.901	0.912	1.008*	0.946
Japan						
R(CW)	0.971	0.976	0.921	0.926	1.013*	0.962
R(sup-ENCNEW)	0.898	0.909	0.868	0.879	1.022*	1.027*
New Zealand						
R(CW)	0.945	0.946	0.915	0.916	0.994	0.962
R(sup-ENCNEW)	0.945	0.775	0.931	0.937	1.001*	0.997
Norway						
R(CW)	0.946	0.951	0.947	0.952	0.951	0.952
R(sup-ENCNEW)	0.916	0.863	0.916	0.798	0.995	0.975
Sweden						
R(CW)	0.928	0.930	0.937	0.939	0.985	0.994
R(sup-ENCNEW)	0.877	0.887	0.846	0.856	1.005*	1.014*
Switzerland						
R(CW)	0.926	0.929	0.921	0.923	0.984	0.978
R(sup-ENCNEW)	0.914	0.945	0.786	0.795	0.976	0.945
UK						
R(CW)	0.958	0.960	0.978	0.980	1.000*	1.022*
R(sup-ENCNEW)	0.965	0.972	0.983	0.991	1.018*	0.994

Note: The predictive regressions of (5), (8) and (11) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}$, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* + \text{regression errors}$ and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors}$, respectively. R(CW) denotes the rolling window size is specified by the CW test; it equals 120. And R(sup-ENCNEW) denotes the rolling window size is chosen by the sup-ENCNEW test. $\frac{\text{RMSE}(\mathcal{M}_1)}{\text{RMSE}(\mathcal{M}_2)}$ denotes the RMSE of random walk ($\mathcal{M}_1$) relative to RMSE of a predictive regression ($\mathcal{M}_2$).* indicates the RMSE ratio is greater than one.

where $q_t \equiv s_t + p_t^* - p_t$ represents the real exchange rate. The rationale of this setting is that the home country targets the purchasing power parity (PPP) level of the exchange rate, defined as the differential between the relative price level of the home country to foreign country $p_t - p_t^*$. Replacing Eq. (3) with Eq. (13), and combining it with Eqs. (4) and (1), we obtain the augmented predictive regression of (5) as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8\eta_t + \text{regression errors}, \tag{14}$$

where $\theta_7 = (1-\phi_i)\phi_q$. Similarly, Eq. (8) can be augmented as:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8\tau_t + \theta_9\gamma_t + \theta_{10}\gamma_t^* + \text{regression errors}. \tag{15}$$

Tables 10 and 11 report the in-sample estimation results of Eqs. (14) and (15). The estimates of θ_7 are insignificant in Canada, Denmark, the Euro Area, Japan, Norway, Sweden, and the UK, which suggests that the real exchange rates are not informative in predicting one-month-ahead exchange rate movements. The exceptions are Australia, New Zealand, and Switzerland, whereas the estimates of θ_7 are negative and significant, both in (14) and (15). This result can be attributed to the common belief that the central bank in Switzerland frequently intervenes in the foreign exchange market, especially after the outbreak of the global financial crisis. Table 12 reports the out-of-sample test results based on the sup-ENCNEW statistics using Eqs. (14) and (15). We find the results are more pronounced than Tables 6 and 7. For example, Eq. (14) outperforms the random walk with drift in eight out of the 10 countries we considered. This suggests that the empirical results obtained from an alternative Taylor rule specification are consistent with those

Table 10
In-sample predictability of liquidity yield when real exchange rate is included in Taylor rule: Estimation results of (14).

	In-sample results								
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	$\overline{R}^2$
Australia	0.399*	0.682*	0.399**	-0.106	-0.544***	0.276	-0.021*	1.903*	0.070
(1999M2–2018M7)	(1.666)	(1.799)	(2.296)	(-0.535)	(-2.890)	(1.501)	(-1.695)	(1.762)	
Canada	-0.603**	0.408	0.156	0.016	0.036	-0.100	0.007	0.954	0.015
(1997M1–2018M12)	(-2.261)	(1.476)	(1.128)	(0.108)	(0.142)	(-0.504)	(0.525)	(0.878)	
Denmark	0.148	0.285	-0.024	-0.019	-0.193	0.143	-0.026	1.014	0.012
(1997M1–2018M12)	(0.446)	(1.157)	(-0.398)	(-0.115)	(-1.122)	(0.904)	(-1.594)	(1.332)	
Euro Area	-1.510***	1.465***	-0.099	0.024	0.257	-0.435***	-0.015	-1.407	0.085
(2000M1–2018M4)	(-3.853)	(4.919)	(-0.688)	(0.121)	(1.320)	(-2.407)	(-0.999)	(-1.172)	
Japan	0.400*	0.186	-0.112	0.144	-0.591	-0.203	-0.029**	3.496***	0.065
(1997M1–2018M8)	(1.914)	(0.947)	(-1.374)	(0.849)	(-0.613)	(-1.445)	(-2.013)	(3.543)	
New Zealand	-0.391	0.690*	-0.060	0.118	-0.007	0.142	-0.031**	-1.009	0.030
(1999M1–2017M10)	(-1.429)	(1.684)	(-0.363)	(0.655)	(-0.021)	(0.572)	(-1.969)	(-1.178)	
Norway	0.743***	0.322	0.100	0.046	-0.045	-0.041	-0.023	1.570**	0.073
(1998M8–2018M8)	(2.854)	(1.243)	(1.339)	(0.281)	(-0.402)	(-0.268)	(-1.513)	(2.310)	
Sweden	-0.231	0.734***	-0.157*	0.165	-0.111	-0.030	-0.012	-0.070	0.035
(1997M1–2018M12)	(-0.860)	(2.491)	(-1.772)	(0.771)	(-0.643)	(-0.181)	(-0.579)	(-0.061)	
Switzerland	-0.523	0.690	0.021	-0.096	-0.092	0.331*	-0.070***	0.798	0.022
(1997M1–2017M10)	(-0.722)	(1.172)	(0.389)	(-0.675)	(-0.293)	(1.876)	(-2.569)	(0.769)	
UK	-0.192	0.483***	0.065	-0.094	-0.276	0.175	-0.022	2.028**	0.025
(1997M8–2018M12)	(-0.438)	(2.765)	(0.487)	(-0.728)	(-1.107)	(0.743)	(-1.006)	(2.325)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8 \eta_t +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

obtained based on the baseline specification, and the out-of-sample forecast results are even better than the benchmark predictive regressions.

5.2. Alternative measure of output gap

Because there is no consensus about which measure of the output gap is used by monetary authorities in their interest-rate rules, we consider an alternative measure of the output gap by constructing the percentage deviation of actual output from a quadratic time trend. We then reestimate Eqs. (5) and (8) and report the in-sample and out-of-sample sup-ENCNEW test statistics in Tables 13–15. It is obvious that the results are quite similar to the benchmark results reported in Section 4.

5.3. Using non-US exchange rates

It is of interest to ask whether our empirical results remain intact if we use non-US countries as a numeraire. We thus use the UK as a benchmark foreign country, and reconstruct the spot rates and forward rates of other countries relative to the UK and redo the in-sample and out-of-sample forecasting exercises.

Following Engel and Wu (2022), we conduct a trilateral cross to obtain the spot and forward rates relative to the UK. For example, the log of AUD per GBP spot exchange rate is constructed as $s_t^{\mathrm{AUD/USD}} - s_t^{\mathrm{GBP/USD}}$. We then report the in-sample and out-of-sample test results based on (5) and (8) in Tables 16–18, respectively. It is worth noting that our univariate regressions use the data of bilateral country pairs, and thus we do not report the results for the US because their statistical inference is intrinsically the same as in our baseline analysis. That is, we only consider eight countries (Australia, Canada, Denmark, the Euro Area, Japan, New Zealand, Norway, Sweden, and Switzerland) in this exercise.

Tables 16 and 17 report the in-sample test results. We find that η_t and τ_t significantly predict the one-period ahead spot rates in seven out of eight countries, but not Switzerland. This result is consistent with a similar exercise reported in Engel and Wu (2022) that liquidity asset demand effects can also be found in non-US countries.[13] Table 18 reports the out-of-sample predictive test results based on the sup-ENCNEW test. However, it seems that the predictive regressions (5) and (8) only outperform the random walk model with drift for Denmark and Japan. Regarding the other countries, the out-of-sample predictive power of liquidity yields on exchange rates is not pronounced.

[13] However, Jiang et al. (2021) find that the empirical links between the liquidity yield and non-US exchange rates are much weaker than those in Engel and Wu (2022), based on quarterly data, and univariate regressions of one currency relative to an average of the others. Engel and Wu (2022) conclude that the essential difference between Jiang et al. (2021) and their findings can be attributed to different data frequency ((Jiang et al., 2021) use quarterly data, while (Engel and Wu, 2022) use monthly data), and different empirical models ((Jiang et al., 2021) use univariate regressions, while (Engel and Wu, 2022) use panel data regressions).

Table 11
In-sample predictability of liquidity yield when real exchange rate is included in Taylor rule: Estimation results of (15).

	In-sample results										
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	$\overline{R}^2$
Australia	0.389*	0.629*	0.378***	-0.094	-0.535***	0.197	-0.019*	3.179*	1.602	0.648	0.080
(1999M2–2018M7)	(1.873)	(1.944)	(2.744)	(-0.482)	(-2.609)	(1.074)	(-1.762)	(1.797)	(0.897)	(0.329)	
Canada	-0.183	0.150	0.158	-0.077	0.089	-0.244	0.019	5.558***	6.356***	0.357	0.120
(1999M8–2018M12)	(-0.627)	(0.558)	(1.471)	(-0.539)	(0.263)	(-0.931)	(1.402)	(4.285)	(3.744)	(0.350)	
Denmark	-0.573	0.230	-0.021	0.071	-0.141	0.180	-0.004	3.003***	4.986***	-0.147	0.035
(1997M1–2018M12)	(-0.948)	(0.377)	(-0.387)	(0.517)	(-0.849)	(1.120)	(-0.254)	(2.661)	(2.814)	(-0.080)	
Euro Area	-1.584***	1.430***	-0.030	-0.067	0.348	-0.484**	-0.018	-0.972	0.071	0.410	0.081
(2000M1–2018M4)	(-3.671)	(4.518)	(-0.182)	(-0.299)	(1.466)	(-2.449)	(-1.102)	(-0.287)	(0.022)	(0.243)	
Japan	-0.769	0.816	-0.090	0.234	0.065	-0.255	-0.020	3.327***	2.181	-2.863***	0.053
(1997M1–2018M8)	(-1.010)	(1.383)	(-1.063)	(1.438)	(0.052)	(-1.430)	(-1.445)	(2.353)	(0.729)	(-2.711)	
New Zealand	-0.420**	0.636*	0.030	0.080	-0.097	0.153	-0.025*	1.150	-0.884	3.929*	0.051
(1999M1–2017M10)	(-2.081)	(1.892)	(0.217)	(0.446)	(-0.414)	(0.747)	(-1.804)	(0.784)	(-1.019)	(1.914)	
Norway	0.646	-0.796	0.039	0.105	-0.019	-0.171	-0.008	3.225***	1.623*	1.805	0.045
(1998M8–2018M8)	(1.590)	(-1.468)	(0.520)	(0.829)	(-0.155)	(-0.910)	(-0.624)	(3.070)	(1.770)	(0.957)	
Sweden	-0.279	0.594**	-0.142*	0.164	-0.149	-0.128	-0.000	3.406**	0.659	3.006	0.069
(1997M1–2018M12)	(-1.081)	(2.057)	(-1.785)	(0.908)	(-0.948)	(-0.767)	(-0.006)	(2.459)	(0.507)	(1.611)	
Switzerland	-0.412	0.334	-0.110	0.039	0.341	0.308*	-0.079**	-1.322	2.417*	-1.614	0.035
(1997M1–2017M10)	(-0.914)	(1.105)	(-1.358)	(0.522)	(0.685)	(1.697)	(-2.306)	(-0.823)	(1.888)	(-0.784)	
UK	-0.384	0.395**	0.066	-0.091	-0.415***	0.146	-0.020	4.547***	2.007*	2.049	0.086
(1997M8–2018M12)	(-1.417)	(2.163)	(0.505)	(-0.605)	(-2.409)	(0.775)	(-1.076)	(3.267)	(1.861)	(1.411)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1 \pi_t + \theta_2 \pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8 \tau_t + \theta_9 \gamma_t + \theta_{10} \gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Table 12
Out-of-sample predictability comparison of models with random walk when real exchange rate is included in Taylor rule: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results				
Home Currency	Compare (14) with driftless RW	Compare (14) with RW with a drift	Compare (15) with driftless RW	Compare (15) with RW with a drift
k	9	8	11	10
Australia	9.992	13.279*	6.707	10.150
Canada	14.604**	17.484**	14.667*	14.185*
Denmark	0.493	0.680	1.079	1.362
Euro Area	20.821***	25.491***	17.813**	21.256**
Japan	29.906***	35.595***	19.775**	24.039***
New Zealand	6.536	10.608	4.714	6.015
Norway	19.444**	19.668***	49.984***	51.304***
Sweden	13.587*	14.928**	21.597**	22.802***
Switzerland	10.060	13.223*	13.263	16.178**
UK	11.117	12.110*	19.130**	19.329**

Note: The predictive regressions of (14) and (15) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8 \eta_t +$ regression errors and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 q_t + \theta_8 \tau_t + \theta_9 \gamma_t + \theta_{10}\gamma_t^* +$ regression errors, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the number of regressors in the small model (random walk). The critical values are 11.226 (10%), 13.831 (5%) and 19.489 (1%) for $k = 8$, 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, 12.502 (10%), 15.408 (5%), and 21.406 (1%) for $k = 10$, for 13.1050 (10%), 16.0986 (5%) and 22.3654 (1%) for $k = 11$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

Table 13
In-sample predictability of liquidity yields when using a quadratic detrending method to construct the output gap: Estimation results of (5).

In-sample results								
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	$\bar{R}^2$
Australia	0.243	0.797**	0.296**	-0.075	-0.425**	0.257	2.501**	0.068
(1999M2–2018M7)	(1.122)	(2.428)	(1.847)	(-0.640)	(-1.999)	(1.157)	(2.400)	
Canada	-0.563**	0.555*	0.032	-0.087	0.387	-0.190	1.066	0.010
(1997M1–2018M12)	(-2.209)	(1.911)	(0.945)	(-1.004)	(0.879)	(-0.769)	(0.832)	
Denmark	-0.598	0.393	-0.051	0.003	-0.073	0.121	0.868	0.000
(1997M1–2018M12)	(-1.029)	(0.630)	(-1.609)	(0.040)	(-0.329)	(0.777)	(1.022)	
Euro Area	-1.578***	1.542***	-0.021	-0.075	0.353	-0.362*	-1.069	0.089
(2000M1–2018M4)	(-4.055)	(5.461)	(-0.993)	(-1.071)	(1.515)	(-1.864)	(-0.935)	
Japan	0.241	0.188	0.007	-0.058	-0.082	-0.077	3.924***	0.051
(1997M1–2018M8)	(1.105)	(1.100)	(0.303)	(-0.886)	(-0.089)	(-0.420)	(3.485)	
Norway	0.631***	0.477*	-0.012	0.015	-0.017	-0.140	1.418*	0.064
(1998M8–2018M8)	(2.773)	(1.887)	(-0.333)	(0.170)	(-0.099)	(-0.638)	(1.946)	
New Zealand	-0.539	0.994**	-0.032	-0.081	0.120	0.020	0.038	0.019
(1999M1–2017M10)	(-1.546)	(2.400)	(-0.387)	(-0.545)	(0.247)	(0.090)	(0.044)	
Sweden	-0.076	1.014***	-0.130***	-0.012	-0.230	0.161	-0.396	0.059
(1997M1–2018M12)	(-0.316)	(3.474)	(-2.676)	(-0.120)	(-0.891)	(1.014)	(-0.387)	
Switzerland	-0.444	0.586***	0.006	-0.030	-0.365	0.180	0.681	0.003
(1997M1–2017M10)	(-1.401)	(2.506)	(0.137)	(-0.489)	(-1.377)	(1.218)	(0.626)	
UK	-0.451	0.728***	-0.039	-0.153**	0.080	0.202	0.440***	0.042
(1997M8–2018M12)	(-1.289)	(3.798)	(-0.645)	(-1.966)	(0.345)	(1.125)	(3.236)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 \eta_t +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

5.4. Combining liquidity yield with other fundamentals

5.4.1. Combining interest rate fundamentals with liquidity yield

Our baseline model considers the Taylor rule fundamentals, which comprises a set of macroeconomic variables including inflation, output gap, and one-period lag of interest rate. However, one may argue that these variables are used to "fit" the interest rate according to a specification motivated by the Taylor rule, and including these variables in a predictive regression might seem unnecessary because we can observe the interest rate directly. For this reason, we consider the following predictive model, which is directly motivated by Eq. (1):

$$\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_3 \eta_t + \text{regression errors.} \tag{16}$$

Table 14
In-sample predictability of liquidity yields when using a quadratic detrending method to construct the output gap: Estimation results of (8).

	In-sample results									
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	$\overline{R}^2$
Australia	0.263	0.684**	0.259**	-0.028	-0.520**	0.128	3.480**	2.761	-0.026	0.079
(1999M2–2018M7)	(1.316)	(2.468)	(2.029)	(-0.306)	(-2.321)	(0.616)	(1.963)	(1.330)	(-0.013)	
Canada	-0.161	0.146	0.071**	-0.123	0.579	-0.381	5.485***	6.162***	0.676	0.127
(1999M8–2018M12)	(-0.543)	(0.563)	(1.955)	(-1.538)	(1.115)	(-1.167)	(3.890)	(3.416)	(0.646)	
Denmark	-0.658	0.300	-0.065***	0.084	-0.291*	0.142	3.098***	5.024***	0.695	0.051
(1997M1–2018M12)	(-1.065)	(0.531)	(-2.389)	(0.903)	(-1.712)	(1.026)	(3.167)	(2.924)	(0.306)	
Euro Area	-1.566***	1.446***	-0.021	-0.061	0.343	-0.461**	0.412	0.580	0.993	0.084
(2000M1–2018M4)	(-3.556)	(5.013)	(-0.743)	(-0.709)	(1.401)	(-2.293)	(0.133)	(0.205)	(0.621)	
Japan	0.209	0.137	0.012	-0.091	-0.062	-0.092	4.568***	2.389	-2.864*	0.046
(1997M1–2018M8)	(0.892)	(0.807)	(0.516)	(-1.064)	(-0.045)	(-0.491)	(2.929)	(0.579)	(-1.852)	
New Zealand	-0.360	0.728**	0.013	0.070	-0.301	-0.077	1.909	-0.221	3.843**	0.043
(1999M1–2017M10)	(-1.644)	(2.311)	(0.214)	(0.636)	(-0.965)	(-0.374)	(1.497)	(-0.253)	(2.264)	
Norway	0.506***	0.398*	-0.028	-0.010	0.024	-0.211	3.173***	1.447*	1.403	0.082
(1998M8–2018M8)	(2.438)	(1.897)	(-0.735)	(-0.100)	(0.148)	(-0.861)	(3.052)	(1.667)	(0.829)	
Sweden	0.083	0.879***	-0.151***	-0.045	-0.322***	0.106	3.774***	-0.756	4.063***	0.109
(1997M1–2018M12)	(0.299)	(3.418)	(-3.021)	(-0.489)	(-1.484)	(0.659)	(2.867)	(-0.584)	(3.362)	
Switzerland	-0.739	1.071*	0.016	0.056	-0.464*	0.176	-0.778	2.779**	-1.663	0.007
(1997M1–2017M10)	(-1.051)	(1.856)	(0.336)	(0.971)	(-1.726)	(1.230)	(-0.491)	(2.049)	(-1.055)	
UK	-0.636**	0.667***	-0.051	-0.171**	-0.017	0.169	5.292***	2.037*	1.905	0.107
(1997M8–2018M12)	(-2.203)	(3.011)	(-0.624)	(-2.206)	(-0.085)	(0.947)	(4.426)	(1.827)	(1.432)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1 \pi_t + \theta_2 \pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7 \tau_t + \theta_8 \gamma_t + \theta_9 \gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Table 15
Out-of-sample predictability comparison of models with random walk when using a quadratic detrending method to construct the output gap: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results				
Home Currency	Compare (5) with driftless RW	Compare (5) with RW with a drift	Compare (8) with driftless RW	Compare (8) with RW with a drift
k	8	7	10	9
Australia	13.777*	15.817**	7.067	8.662
Canada	23.404***	28.483***	24.356***	31.673***
Denmark	2.169	2.961	4.120	4.698
Euro Area	12.426*	16.085**	11.630	14.173*
Japan	16.815**	19.894***	16.089**	18.185**
New Zealand	2.335	2.986	1.093	1.176
Norway	16.046*	16.448**	19.584**	21.330***
Sweden	16.299**	19.584***	24.081***	25.668***
Switzerland	0.597	0.700	2.579	2.974
UK	11.309*	13.058**	17.110**	17.923**

Note: The predictive regressions of (5), (8) and (11) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}$, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* + \text{regression errors}$ and $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \text{regression errors}$, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the number of regressors in the small model (random walk). The critical values are 10.466(10%), 12.968(5%), and 18.406 (1%) for $k = 7$, 11.226 (10%), 13.831 (5%) and 19.489 (1%) for $k = 8$, 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, 12.502 (10%), 15.408 (5%), and 21.406 (1%) for $k = 10$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

Table 16
In-sample predictability of liquidity yield: Estimation results of (5) using UK as numeraire.

In-sample results								
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	$\bar{R}^2$
Australia	0.326*	0.125	0.115	0.287	-0.602*	0.277	0.506***	0.057
(1999M2–2018M7)	(1.665)	(0.354)	(0.784)	(1.580)	(-1.932)	(1.318)	(3.904)	
Canada	-0.581***	0.291	0.103	0.059	0.023	0.102	3.248***	0.049
(1997M8–2018M12)	(-2.848)	(1.558)	(0.918)	(0.471)	(0.088)	(0.588)	(3.002)	
Denmark	0.099	0.057	-0.013	0.008	-0.044	-0.051	2.431***	0.075
(1997M8–2018M12)	(0.397)	(0.257)	(-0.232)	(0.071)	(-0.199)	(-0.335)	(3.391)	
Euro Area	0.094	0.001	-0.054	0.028	0.001	-0.087	2.228**	-0.008
(2000M1–2018M4)	(0.274)	(0.004)	(-0.339)	(0.093)	(0.002)	(-0.407)	(2.172)	
Japan	0.414**	0.047	-0.078	0.009	0.543	-0.303***	5.897***	0.115
(1997M8–2018M8)	(2.127)	(0.149)	(-1.020)	(0.041)	(0.461)	(-2.535)	(4.163)	
New Zealand	-0.348	0.138	-0.010	0.241	0.230	-0.082	0.440***	0.054
(1999M1–2017M10)	(-1.143)	(0.352)	(-0.071)	(1.099)	(0.512)	(-0.264)	(4.078)	
Norway	0.093	0.145	0.634	0.020	-0.089	0.073	1.683**	0.011
(1999M1–2017M10)	(0.574)	(0.675)	(0.725)	(0.173)	(-0.937)	(0.747)	(2.074)	
Sweden	-0.240*	0.153	-0.059	0.151	-0.008	0.113	2.167***	0.020
(1997M8–2018M12)	(-1.662)	(0.753)	(-0.889)	(0.827)	(-0.057)	(0.864)	(3.199)	
Switzerland	-0.349	0.083	0.050	-0.143	-0.220	0.158	-0.009	-0.007
(1997M8–2017M10)	(-1.338)	(0.322)	(1.443)	(-1.461)	(-0.769)	(1.208)	(-0.010)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t + \text{regression errors}$. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

Similarly, we also consider the role of foreign exchange swap market frictions in predicting the exchange rate by combining Eq. (16) with Eq. (7):

$$\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_3\tau_t + \theta_4\gamma_t + \theta_5\gamma_t^* + \text{regression errors}. \tag{17}$$

Eqs. (16) and (17) include interest rates in the home and foreign countries, and liquidity yield as predictors of the one-period-ahead exchange rate. Many empirical studies on exchange rate predictability such as Molodtsova and Papell (2009),Molodtsova and Papell (2013), and Rossi (2013) also consider a specification with i_t and i_t^* as predictors. As it is motivated by UIP, their predictive regression is also called a UIP regression. Our specification can therefore be understood as a standard UIP regression augmented with the liquidity yield, foreign exchange swap market frictions, and country-specific liquidity yield as additional predictors.

We then report the in-sample and out-of-sample predicting results based on Eqs. (16) and (17) in Tables 19–21. According to Tables 19 and 20, we do not generally find that θ_1 and θ_2 are significant, indicating that the interest rates do not have in-sample

Table 17
In-sample predictability of liquidity yield: Estimation results of (8) using UK as numeraire.

In-sample results										
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	$\overline{R}^2$
Australia	0.246	0.269	0.154	0.250	-0.685*	0.243	0.529***	4.202**	-3.720***	0.067
(1999M2–2018M7)	(1.148)	(0.749)	(0.973)	(1.563)	(-1.826)	(1.057)	(4.244)	(2.144)	(-3.061)	
Canada	-0.414*	0.137	0.125	-0.048	0.153	-0.013	5.497***	5.639***	-3.570***	0.074
(1999M8–2018M12)	(-1.783)	(0.585)	(1.129)	(-0.366)	(0.578)	(-0.065)	(4.806)	(4.039)	(-4.165)	
Denmark	0.175	-0.284	-0.010	-0.061	-0.194	-0.031	4.475***	4.295***	-0.911	0.121
(1997M8–2018M12)	(0.731)	(-1.154)	(-0.176)	(-0.517)	(-0.896)	(-0.152)	(4.561)	(4.474)	(-1.135)	
Euro Area	-0.042	0.175	-0.012	0.009	-0.088	-0.119	3.825**	0.243	-0.175	-0.004
(2000M9–2018M4)	(-0.133)	(0.614)	(-0.066)	(0.027)	(-0.341)	(-0.530)	(1.964)	(0.135)	(-0.193)	
Japan	0.288	-0.059	-0.099	-0.025	1.419	-0.609***	8.091***	-2.445	-3.447**	0.143
(1997M8–2018M8)	(1.206)	(-0.180)	(-1.386)	(-0.113)	(0.840)	(-3.597)	(4.403)	(-0.646)	(-2.333)	
New Zealand	-0.461	0.379	0.009	0.290	0.496	-0.186	0.461***	-0.299	-1.379	0.051
(1999M1–2017M10)	(-1.425)	(0.809)	(0.064)	(1.250)	(1.067)	(-0.604)	(4.357)	(-0.330)	(-0.916)	
Norway	0.073	0.199	0.060	0.022	-0.060	0.016	2.320*	1.197	-1.279	0.007
(1999M1–2017M10)	(0.467)	(0.687)	(0.636)	(0.207)	(-0.599)	(0.124)	(1.651)	(0.962)	(-1.574)	
Sweden	-0.179	0.380*	-0.055	0.150	0.572	-0.002	4.232***	0.523	-1.368**	0.037
(1997M8–2018M12)	(-1.260)	(1.846)	(-0.846)	(0.829)	(0.937)	(-0.183)	(5.301)	(0.797)	(-2.453)	
Switzerland	-0.360	0.346	0.055*	-0.095	-0.392	0.144	0.285	-0.180	-1.840***	0.008
(1997M8–2017M10)	(-1.380)	(1.578)	(1.715)	(-0.997)	(-0.530)	(1.147)	(0.197)	(-0.287)	(-2.878)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected *t*-ratios. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

Table 18
Out-of-sample comparisons between models with liquidity yields and random walks using UK as numeraire: Rossi and Inoue (2012)'s sup-ENCNEW test.

Out-of-sample results				
Home Currency	Compare (5) with driftless RW	Compare (5) with RW with a drift	Compare (8) with driftless RW	Compare (8) with RW with a drift
k	8	7	10	9
Australia	10.023	9.558	10.418	10.270
Canada	8.714	9.161	8.482	10.876
Denmark	12.977*	14.103**	19.936**	21.955***
Euro Area	-0.797	-0.181	-0.524	-0.126
Japan	29.545**	30.363***	27.130***	27.937***
New Zealand	8.628	7.500	9.155	8.091
Norway	3.601	4.813	4.878	6.976
Sweden	2.844	5.283	7.255	9.501
Switzerland	-0.472	-0.846	0.077	-0.803

Note: The predictive regressions of (5) and (8) are $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\eta_t +$ regression errors, $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t + \theta_8\gamma_t + \theta_9\gamma_t^* +$ regression errors, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the small model (random walk). The critical values are 10.466(10%), 12.968(5%), and 18.406 (1%) for $k = 7$, 11.226 (10%), 13.831 (5%) and 19.489 (1%) for $k = 8$, 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, 12.502 (10%), 15.408 (5%), and 21.406 (1%) for $k = 10$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at 10%, 5%, and 1% significance level, respectively.

predicting power for the change in the exchange rate. This is consistent with the empirical findings in Engel et al. (2019) that the interest rate typically does not predict the exchange rate. The sup-ENCNEW statistics in Table 21 show that Eq. (20) performs better than Eq. (19) in predicting the change in the exchange rate, and indicate that five out of 10 currencies are predictable, compared with a random walk model with or without drift. Finally, for the sake of comparison, we also investigate the predictive power of a UIP regression with only i_t and i_t^* as predictors:

$$\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \text{regression errors}. \tag{18}$$

The fifth and sixth columns of Table 21 show that Eq. (18) outperforms the random walk in only two out of 10 currencies (New Zealand and the UK), which implies that the UIP regression has weak out-of-sample predictive power. Moreover, its performance is also worse than the model with only Taylor rule fundamentals in terms of the sup-ENCNEW test, compared with Table 7. Again, this implies that the macroeconomic variables in the Taylor rule fundamentals, such as inflation and output gap, can deliver more information beyond the interest rate, and thus help to predict future exchange rate movements.

Table 19
In-sample predictability of model based on interest rate fundamentals and liquidity yields: Empirical results of (16).

In-sample results				
Home Country	θ_1	θ_2	θ_3	$\overline{R}^2$
Australia	-0.116	0.204	2.402**	0.011
(1999M1–2018M11)	(-0.548)	(1.416)	(2.108)	
Canada	-0.125	0.118	0.852	-0.004
(1997M1–2018M12)	(-0.450)	(0.584)	(0.605)	
Denmark	-0.120	0.117	0.994	0.004
(1997M1–2018M12)	(-0.683)	(0.739)	(1.298)	
Euro Area	-0.167	0.136	-0.641	-0.008
(1999M1–2018M11)	(-1.013)	(0.939)	(-0.376)	
Japan	0.099	-0.155	3.516***	0.051
(1997M1–2018M12)	(0.104)	(-1.218)	(3.395)	
New Zealand	-0.026	0.136	0.385	-0.007
(1999M1–2018M11)	(-0.132)	(0.740)	(0.456)	
Norway	-0.025	0.038	1.295	0.004
(1998M7–2018M12)	(-0.184)	(0.268)	(1.544)	
Sweden	-0.135	0.181	0.572	-0.003
(1997M1–2018M12)	(-0.817)	(1.190)	(0.657)	
Switzerland	-0.415**	0.229	0.373	0.005
(1997M1–2018M12)	(-2.165)	(1.468)	(0.318)	
UK	-0.141	0.185	2.286***	0.015
(1997M7–2018M12)	(-0.883)	(1.010)	(2.813)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_3 \eta_t +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Table 20
In-sample predictability of model based on interest rate fundamentals and liquidity yields: Empirical results of (17).

In-sample results						
Home Country	θ_1	θ_2	θ_3	θ_4	θ_5	$\overline{R}^2$
Australia	-0.334	0.205	2.842	4.029*	-0.049	0.038
(1999M1–2018M11)	(-1.511)	(1.175)	(1.535)	(1.937)	(-0.020)	
Canada	0.022	-0.102	5.432***	6.014***	0.494	0.122
(1999M8–2018M12)	(0.069)	(-0.430)	(4.325)	(3.519)	(0.425)	
Denmark	-0.200	0.208	3.153***	5.030***	0.109	0.050
(1997M1–2018M12)	(-1.248)	(1.322)	(2.613)	(2.855)	(0.064)	
Euro Area	-0.176	-0.115	2.500	2.291	0.993	0.001
(2000M9–2018M11)	(-0.956)	(-0.631)	(0.914)	(0.869)	(0.387)	
Japan	-0.042	-0.190	3.828***	3.301	-3.048**	0.044
(1997M1–2018M12)	(-0.037)	(-1.131)	(2.715)	(1.155)	(-2.373)	
New Zealand	-0.078	0.104	2.162	0.415	3.229	0.024
(1999M1–2018M11)	(-0.442)	(0.669)	(1.500)	(0.425)	(1.436)	
Norway	-0.062	-0.151	3.367***	1.904**	2.380	0.048
(1998M7–2018M12)	(-0.508)	(-0.839)	(2.928)	(2.100)	(1.241)	
Sweden	-0.243*	0.040	4.517***	0.972	3.300**	0.055
(1997M1–2018M12)	(-1.832)	(0.262)	(3.285)	(0.900)	(2.012)	
Switzerland	-0.332	0.266**	-0.617	1.952	-1.195	0.010
(1997M1–2018M12)	(-1.389)	(2.056)	(-0.458)	(1.245)	(-0.652)	
UK	-0.249**	0.102	4.980***	1.928**	1.961	0.083
(1997M7–2018M12)	(-1.981)	(0.669)	(3.611)	(2.073)	(1.449)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_3 \tau_t + \theta_4 \gamma_t + \theta_5 \gamma_t^* +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

We thus conclude that the foreign exchange swap market frictions and country-specific liquidity yield can provide more information about the change in exchange rates, after controlling the interest rate fundamentals. We also find that the interest rate does not have much power in predicting the exchange rate, in both in-sample and out-of-sample tests. Engel et al. (2019) offer a possible explanation of this phenomenon using an open-economy New Keynesian model to illustrate that the interest rate could rise because of a tightened (positive) monetary policy shock, or a negative liquidity shock to home government bonds. However, these two shocks can have opposite effects on the exchange rate. The former causes the home currency to appreciate, while the latter depreciates it. Thus, the interplay between these two shocks can generate an ambiguous effect on the exchange rate, which makes the interest rate a weaker predictor of future changes in the exchange rate.

Table 21
Out-of-sample comparison of between interest rate models with liquidity yields and random walks: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results						
Home currency	Compare (16) with driftless RW	Compare (16) with RW with a drift	Compare (17) with driftless RW	Compare (17) with RW with a drift	Compare (18) with driftless RW	Compare (18) with RW with a drift
k	4	3	6	5	3	2
Australia	3.111	2.150	0.394	0.102	3.034	1.382
Canada	18.425***	17.186***	28.035***	27.250***	4.966	3.762
Denmark	-0.342	0.335	4.243	5.268	2.399	3.136
Euro Area	0.538	1.945	8.455	8.793	0.538	3.009
Japan	12.771**	12.568	10.823*	12.459*	0.735	3.533
New Zealand	9.805*	8.801*	4.801	8.638	7.430*	6.925*
Norway	6.324	4.072	12.119*	10.025*	2.703	2.007
Sweden	-0.214	3.159	14.774**	16.505***	2.380	3.159
Switzerland	3.202	2.473	4.973	4.002	2.838	3.431
UK	6.288	6.365	14.553**	16.910***	14.774**	6.717*

Note: The predictive regression of (16), (17) and (18) are $\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_7 \eta_t + \text{regression errors}$, $\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \theta_3 \tau_t + \theta_4 \gamma_t + \theta_5 \gamma_t^* + \text{regression errors}$ and $\Delta s_{t+1} = \theta_0 + \theta_1 i_t + \theta_2 i_t^* + \text{regression errors}$, respectively. k denotes the difference between the number of regressors in the large (alternative) model and the small model (random walk). The critical values are 5.624 (10%), 7.194 (5%) and 10.710 (1%) for $k = 2$, 6.908 (10%), 8.677(5%), and 12.615 (1%) for $k = 3$, 7.942 (10%), 9.980 (5%) and 14.451 (1%) for $k = 4$, 8.892 (10%), 11.090 (5%), and 15.748 (1%) for $k = 5$, 9.703 (10%), 12.030 (5%) and 17.132 (1%) for $k = 6$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

5.4.2. *Combining monetary fundamental with liquidity yield*

We also incorporate Eq. (1) into the conventional monetary model of exchange rate determination to derive alternative empirical specifications. The conventional flexible-price monetary model includes the money demand functions of the home and foreign countries, and assuming UIP and PPP hold. Specifically, the money market equilibria in the home and foreign countries are given by:

$$m_t - p_t = \phi y_t - \lambda i_t, \tag{19}$$

$$m_t^* - p_t^* = \phi y_t^* - \lambda i_t^*, \tag{20}$$

where m_t,p_t, and y_t are the logs of money supply, price level, and output, respectively, i_t denotes the interest rate, and asterisks denote foreign country variables. The parameters ϕ and λ represent the income elasticity of money demand and the semi-elasticity of the interest rate with respect to money demand, respectively. Subtracting (20) from (19) and using Eq. (1) to replace the UIP condition and assuming the PPP condition $s_t = p_t - p_t^*$ holds, we obtain:

$$\mathrm{E}_t s_{t+1} - s_t = -\frac{1}{\lambda}\left(f_t^M - s_t\right) + \eta_t, \tag{21}$$

where $f_t^M = (m_t - m_t^*) - \phi(y_t - y_t^*)$ denotes the monetary fundamentals. We thus use the following predictive regression to evaluate the exchange rate predictability implied by Eq. (21) as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1 \left(f_t^M - s_t\right) + \theta_2 \eta_t + \text{regression errors}. \tag{22}$$

The term $f_t^M - s_t$ can be considered as an "error-correction" term that captures the current deviation of exchange rate from its fundamental value, which may contain information about future exchange rate movements (Mark, 1995). Eq. (22) can be viewed as an augmented predictive regression model used in Mark (1995), after including η_t as an additional predictive variable. If we set $\theta_2 = 0$, Eq. (22) is reduced to a standard model with monetary fundamentals as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1 \left(f_t^M - s_t\right) + \text{regression errors}. \tag{23}$$

We also investigate the role of deviations from CIP, and the liquidity yields of home and foreign government by substituting Eq. (7) into Eq. (22) to replace η_t:

$$\Delta s_{t+1} = \theta_0 + \theta_1 \left(f_t^M - s_t\right) + \theta_2 \tau_t + \theta_3 \gamma_t + \theta_4 \gamma_t^* + \text{regression errors}. \tag{24}$$

To construct the monetary fundamental f_t^M, we follow Mark (1995) to set $\phi = 1$, that is, $f_t^M = (m_t - m_t^*) - (y_t - y_t^*)$. The monthly, seasonally adjusted M2 data are used as the money supply measure for all countries, while industrial production is used to measure real output. The M2 and industrial production data are obtained from Datastream and IFS, respectively.

Tables 22 and 23 report the in-sample predictability of exchange rate movements for liquidity yields based on Eqs. (22) and (24), respectively. The forecasting performance of η_t,τ_t, and γ_t is similar to our benchmark results reported in Tables 1 and 2. For instance, τ_t

Table 22
In-sample predictability of the models with monetary fundamental and liquidity yield: Estimation results of (22).

In-sample results			
	θ_1	θ_2	$\overline{R}^2$
Australia	0.008	1.749	0.011
(1999M1–2017M6)	(1.004)	(1.608)	
Canada	0.008	0.701	0.003
(1997M1–2018M12)	(1.009)	(0.590)	
Denmark	0.007	1.267*	0.012
(1997M1–2018M12)	(1.188)	(1.704)	
Euro Area	0.018	-0.772	0.007
(2000M1–2018M4)	(1.591)	(-0.326)	
Japan	0.007	2.899**	0.047
(1997M1–2018M8)	(0.560)	(3.152)	
Norway	0.007	0.601	-0.007
(2008M1–2018M8)	(0.880)	(0.456)	
Sweden	0.011	-0.152	0.002
(1998M1–2018M12)	(1.384)	(-0.153)	
Switzerland	0.008	1.238	0.007
(1997M1–2017M10)	(1.648)	(1.282)	
UK	-0.001	2.131**	0.014
(1997M7–2018M12)	(-0.142)	(2.510)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1(f_t^M - s_t) + \theta_2\eta_t + \text{regressionerrors}$, where $f_t^M = (m_t - m_t^*) - (y_t - y_t^*)$. The numbers in parentheses are Newey-West corrected *t*-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

significantly predicts the exchange rate movements in Australia, Canada, Denmark, Japan, Norway, Sweden, and the UK. Furthermore, $f_t^M - s_t$ does not have any predictive power for one-month-ahead exchange rate movements for any of the countries, which is consistent with the previous empirical findings documented by Mark (1995) and Kilian (1999) that monetary fundamentals usually fail to predict short-run exchange rate movements. The out-of-sample results based on the sup-ENCNEW test are reported in Table 24, and are close to the benchmark results in Table 7. For example, Eq. (24) outperforms the random walk with drift in five out of 10 countries, while results from Eq. (8) show that the exchange rate changes in six out of 10 countries are predictable. In sum, we conclude that the predictive power of liquidity yields on exchange rate movements is robust when controlling monetary fundamentals.

5.5. Alternative measure of liquidity yield

In this subsection, we consider two alternative measures of liquidity yields to check the robustness of our results. First, we follow Du et al. (2018a) to consider the overnight indexed swap (OIS) rate to reconstruct τ_t, γ_t, and γ_t^*. The OIS rate is indexed to the overnight rate, which contains very little credit risk and is unaffected by frictions in the LIBOR interest-rate swap rate. Second, we follow Nagel (2016) and use the spread between the general collateral (GC) repo rate and three-month Treasury bill rate to measure the liquidity yield. Nagel (2016) argues that if Treasury bonds themselves are default free, then Treasury GC repos are free of credit risk because they are secured by Treasury bonds. However, repos are not as liquid as Treasury bills because the money is always lent for a term; thus, the GC repo–Treasury bill spread mainly captures the liquidity yields of Treasury bills.

5.5.1. Using OIS to construct the liquidity yield

Let RET_t^{OIS} and RET_t^{OIS*} represent the OIS rates for home currency and foreign currency, respectively. We can rewrite η_t as follows:

$$\eta_t = \tau_t^{OIS} + \gamma_t^{OIS} - \gamma_t^{OIS*}, \tag{25}$$

where $\tau_t^{OIS} = (f_t - s_t) - (RET_t^{OIS} - RET_t^{OIS*})$ denotes the CIP deviations measured by OIS rates, and $\gamma_t^{OIS} = RET_t^{OIS} - i_t$ and $\gamma_t^{OIS*} = RET_t^{OIS} - i_t^*$ denote the OIS–Treasury spread of the home country and foreign countries, which are used to proxy the liquidity of the home and foreign government bonds.

We obtain the one-year tenor OIS rate from Bloomberg and construct $\tau_t^{OIS}, \gamma_t^{OIS}$, and γ_t^{OIS*}. Because the monthly OIS rate data for Denmark, Norway, and Sweden are unavailable before the global financial crisis, we restrict our analysis to Australia, Canada, New Zealand, Japan, Switzerland, and the UK. We then use $\tau_t^{OIS}, \gamma_t^{OIS}$, and γ_t^{OIS*} to replace τ_t, γ_t, and γ_t^* in Eq. (8), and reexamine the in-sample and out-of-sample exchange rate predictability. We plot $\tau_t^{OIS}, \gamma_t^{OIS}$, and γ_t^{OIS*} together with η_t for Australia, Canada, the Euro Area, New Zealand, Japan, Switzerland, and the UK in Fig. 3. Note that the sample periods are relatively short (typically starting from 2002) because of data limitations.

Table 25 reports the in-sample predictability results. In Japan and the UK, we find τ_t^{OIS} significantly predicts exchange rate movements. However, γ_t^{OIS} only predicts the exchange rate in Switzerland, which can be understood from Fig. 3, where γ_t^{OIS} and γ_t^{OIS*}

Table 23
In-sample predictability of the models with monetary fundamental and liquidity yields: Estimation results of (24).

In-sample results					
	θ_1	θ_2	θ_3	θ_4	$\overline{R}^2$
Australia	0.006	3.085*	2.774	0.674	0.037
(1999M1–2017M6)	(0.707)	(1.771)	(1.116)	0.270)	
Canada	-0.001	5.468***	6.339***	0.216	0.122
(1999M8–2018M12)	(-0.168)	(4.430)	(4.038)	(0.189)	
Denmark	-0.004	3.474***	5.494***	-0.143***	0.047
(1997M1–2018M12)	(-0.737)	(3.732)	(3.878)	(-0.128)	
Euro Area	0.020	0.403	3.138	1.918	0.009
(2000M9–2018M4)	(1.623)	(0.148)	(0.315)	(0.055)	
Japan	0.009	2.653**	3.604	-3.681***	0.043
(1997M1–2018M12)	(0.766)	(2.434)	(1.290)	(-3.189)	
Norway	0.004	5.052**	2.853**	2.839	0.078
(2008M1–2018M8)	(0.476)	(2.266)	(2.344)	(1.196)	
Sweden	0.013*	4.342***	0.122	2.977*	0.069
(1998M1–2018M12)	(1.691)	3.487)	(0.096)	(1.801)	
Switzerland	0.007	0.690	2.476*	-1.299	0.009
(1997M1–2018M12)	(1.157)	(0.693)	(2.175)	(-0.894)	
UK	-0.009	4.704***	2.652**	0.797	0.072
(1997M7–2018M12)	(-1.538)	(3.419)	(2.428)	(0.700)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1(f_t^M - s_t) + \theta_2\tau_t + \theta_3\gamma_t + \theta_4\gamma_t^* +$ regressionerrors, where $f_t^M = (m_t - m_t^*) - (y_t - y_t^*)$. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

Table 24
Out-of-sample predictability comparison of monetary models with liquidity yields with random walk: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results						
Home Currency	Compare (22) with driftless RW	Compare (22) with RW with a drift	Compare (24) with driftless RW	Compare (24) with RW with a drift	Compare (23) with driftless RW	Compare (23) with RW with a drift
k	3	2	5	4	2	1
Australia	0.839	3.280	5.280	5.209	0.837	3.407
Canada	10.210**	12.114***	27.263***	25.534***	0.105	1.601
Denmark	1.064	1.186	2.882	3.414	0.461	0.749
Euro Area	2.284	3.043	3.830	7.195	2.284	7.360**
Japan	14.196***	18.369***	18.572***	22.890***	3.016	9.528
Norway	3.631	2.155	13.734***	13.080**	0.829	0.503
Sweden	0.446	1.165	5.163	6.842	0.576	2.302
Switzerland	5.619	7.333**	6.546	9.230*	-0.098	2.541
UK	2.225	3.094	15.091**	15.401***	-0.321	0.217

Note: The predictive regressions (22) and (24) are $\Delta s_{t+1} = \theta_0 + \theta_1\left(f_t^M - s_t\right) + \theta_2\eta_t +$ regression errors and $\Delta s_{t+1} = \theta_0 + \theta_1\left(f_t^M - s_t\right) + \theta_2\tau_t + \theta_3\gamma_t + \theta_4\gamma_t^* +$ regression errors, respectively. The standard monetary model (23) represents a predictive regression as $\Delta s_{t+1} = \theta_0 + \theta_1\left(f_t^M - s_t\right) +$ regression errors. $f_t^M = (m_t - m_t^*) - (y_t - y_t^*)$. k denotes the difference between the number of regressors in the large (alternative) model and the number of regressors in the small model (random walk). The critical values are 3.938 (10%), 5.211 (5%) and 8.125 (1%) for $k = 1$, 5.624 (10%), 7.194 (5%) and 10.710 (1%) for $k = 2$, 6.908(10%), 8.677(5%), and 12.615 (1%) for $k = 3$, 7.942 (10%), 9.980 (5%) and 14.451 (1%) for $k = 4$, 8.892 (10%), 11.090 (5%), and 15.748 (1%) for $k = 5$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

follow a similar trend, and have moved closer together after the 2008–09 global financial crisis. Meanwhile, the effects of γ_t^{OIS} and γ_t^{OIS*} could be offset by each other and these variables do not deliver useful information about future exchange rate movements. As for the out-of-sample forecasting performance, we report the sup-ENCNEW test statistics in Table 26. The results indicate that the model outperforms a random walk with a drift in Australia, Canada, the Euro Area, and Japan. In sum, when using the OIS rate instead of LIBOR to construct the frictions in the forward swap market, and the liquidity of home and foreign government bonds, the predictive power of the model is somewhat weaker than our baseline measure of liquidity yields. However, given the short sample period and the lack of data for many countries, these results should be interpreted with caution.

5.5.2. Using the conventional measure of liquidity yield

Following Nagel (2016), we use the GC repo–Treasury bill spread to proxy the liquidity of government bonds of the home and foreign countries, and investigate their predictive power for one-month-ahead exchange rate changes. We denote $\gamma_t^{Nagel} = i_t^{GC} - i_t^{Tbill}$ and

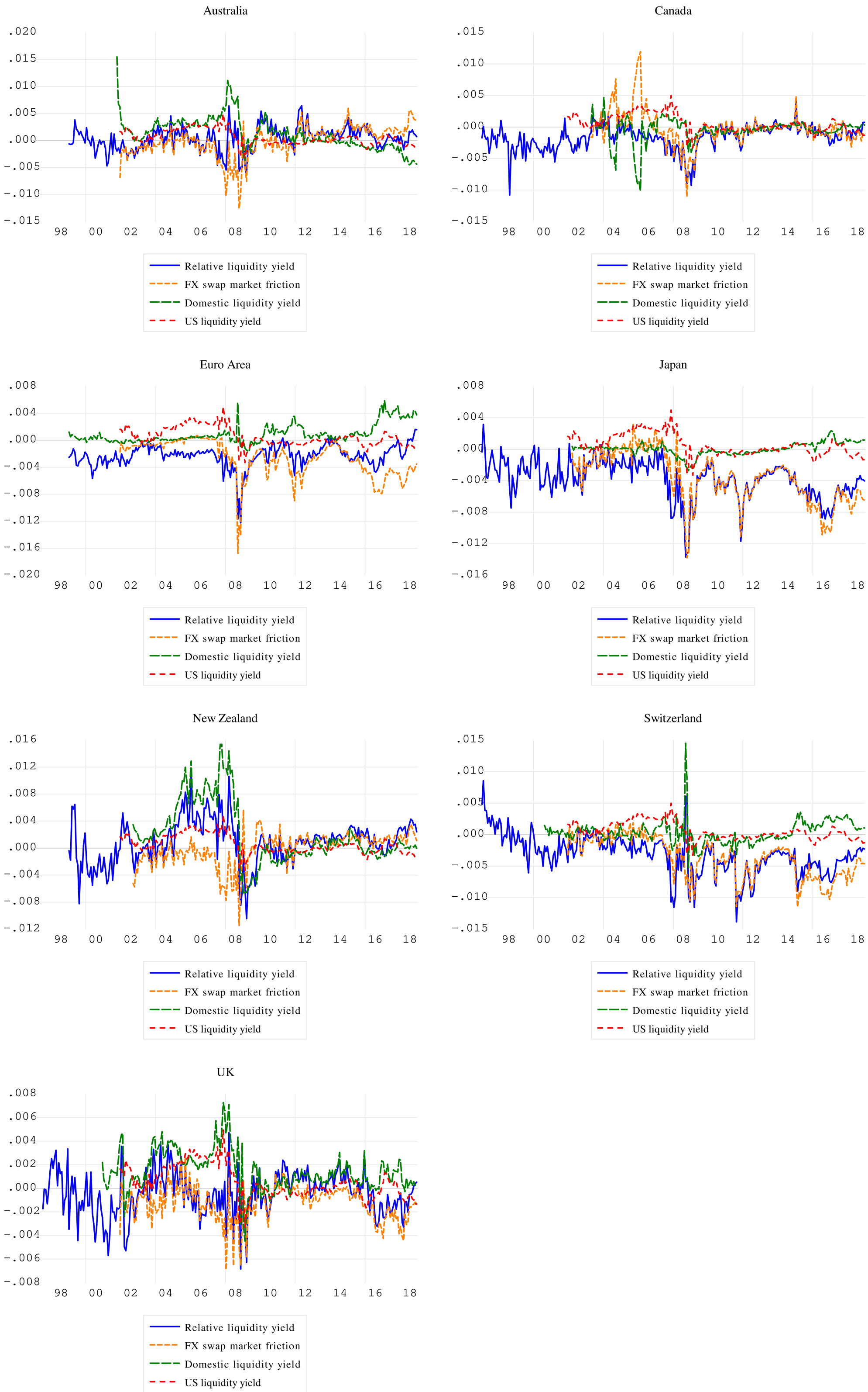

Fig. 3. Plots of the relative liquidity yield η_t, together with OIS-based foreign exchange market frictions τ_t^{OIS}, and the measures of country-specific liquidity of government bonds γ_t^{OIS} and γ_t^{OIS*}.

Table 25
In-sample predictability of OIS liquidity yield.

	In-sample results									
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	$\overline{R}^2$
Australia	-0.057	0.853**	0.319	-0.075	-0.849**	-0.296	0.629	3.731	3.369	0.069
(2001M12–2018M9)	(-0.106)	(2.366)	(1.374)	(-0.385)	(-2.056)	(-1.035)	(0.426)	(1.140)	(0.770)	
Canada	-0.726*	0.555	0.257	-0.047	-0.160	-0.154	0.971	1.888	-1.359	0.030
(2003M4–2018M12)	(-1.691)	(1.612)	(1.346)	(-0.238)	(-0.403)	(-0.544)	(0.665)	(1.419)	(-0.479)	
Euro Area	-1.531***	1.420***	-0.158	0.039	0.537	-0.893***	-1.173	2.041	3.994	0.090
(2001M12–2018M4)	(-3.416)	(4.306)	(-1.029)	(0.191)	(1.318)	(-2.560)	(-0.832)	(0.590)	(1.004)	
Japan	0.228	0.290	-0.218***	0.279*	0.045	-0.426	2.808***	4.710	-1.618	0.060
(2002M3–2018M12)	(1.088)	(1.287)	(-2.714)	(1.684)	(0.032)	(-1.564)	(2.823)	(1.033)	(-0.534)	
New Zealand	-0.172	0.617	-0.247	0.108	-0.168	-0.955	-0.599	0.553	0.553	10.513
(2002M9–2017M10)	(-0.520)	(1.540)	(-1.042)	(0.485)	(-0.491)	(-1.604)	(-0.333)	(0.209)	(1.438)	
Switzerland	-0.627*	0.766***	0.010	-0.197	0.034	-0.302	-0.549	2.811**	2.521	0.018
(2001M12–2018M12)	(-1.692)	(2.723)	(0.187)	(-1.426)	(0.083)	(-1.145)	(-0.415)	(2.003)	(0.802)	
UK	-0.189	0.511**	0.070	-0.025	-0.021	0.159	2.740**	2.135	-7.377*	0.037
(2001M12–2018M12)	(-0.471)	(2.492)	(0.451)	(-0.174)	(-0.086)	(0.912)	(2.379)	(1.138)	(-1.664)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t^{OIS} + \theta_8\gamma_t^{OIS} + \theta_9\gamma_t^{OIS*} +$ regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

Table 26
Out-of-sample predictability comparison of models with OIS liquidity yields and random walk: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results		
Home Currency	Compare (8) with driftless RW	Compare (8) with RW with a drift
k	10	9
Australia	20.424**	20.896***
Canada	23.239***	24.065***
Euro Area	16.334**	21.166***
Japan	11.761	13.980*
New Zealand	5.013	6.628
Switzerland	0.537	2.62
UK	8.924	9.738

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1} + \theta_6 i_{t-1}^* + \theta_7\tau_t^{OIS} + \theta_8\gamma_t^{OIS} + \theta_9\gamma_t^{OIS*} +$ regression errors. k denotes the difference between the number of regressors in the large (alternative) model and the small model (random walk). The critical values are 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, 12.502 (10%), 15.408 (5%), and 21.406 (1%) for $k = 10$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

$\gamma_t^{Nagel*} = i_t^{GC*} - i_t^{Tbill*}$ as the GC repo–Treasury bill spread of the home and foreign countries, and we estimate the predictive regression as follows:

$$\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1}^{Tbill} + \theta_6 i_{t-1}^{Tbill*} + \theta_7\gamma_t^{Nagel} + \theta_8\gamma_t^{Nagel*} + \text{regression errors}. \tag{26}$$

Because of data limitations, we restrict our exercise to Canada and Japan only. To construct the GC repo–Treasury bill spread, we obtain the three-month Treasury GC repo rates of Japan and the US from Bloomberg, and the CORRA overnight GC repo rates of Canada from Datastream. The three-month Treasury bill rates are obtained from IFS. The constructed γ_t^{Nagel} for Canada and Japan, and γ_t^{Nagel*} for the US are plotted in Fig. 4.

The in-sample and out-of-sample prediction results are reported in Tables 27 and 28. It is clear that γ_t^{Nagel} significantly predicts exchange rate movements in Canada and Japan, and the out-of-sample tests indicate the predictive model outperforms a random walk with or without drift for both countries. We thus conclude that the alternative measure of liquidity yield proposed by Nagel (2016) also predicts future exchange rates.

6. Long-horizon predictability

In this section, we examine long-horizon nominal exchange rate predictability based on the model with liquidity yields in light of the extant literature employing long-horizon predictive regressions to evaluate exchange rate predictability based on economic fundamentals (Kilian, 1999; Berkowitz and Giorgianni, 2001; Engel et al., 2007; Wu and Wang, 2012; Mark, 1995; Engel and Wu, 2023). Note that there are some potential pitfalls in the statistical inference in the assessment of long-horizon forecasts using the long-horizon predictive regression. For example, there may exist serial correlation in the disturbance term induced by the overlapping observations in the dependent variables, and a serious size distortion when making inferences based on standard asymptotic distribution theory. For these reasons, we follow Rapach and Wohar (2006),Rapach and Wohar (2005), and Engel and Wu (2023) in using a bootstrap procedure with heteroscedastic autocorrelation robust standard errors to overcome this problem.

We include the liquidity yield as an additional predictor in the long-horizon regression with Taylor rule fundamentals proposed by Engel et al. (2007). Specifically, the long-horizon predictive model is:

$$s_{t+h} - s_t = \theta_0^h + \theta_{TR}^h TR_t + \theta_\eta^h \eta_t + \epsilon_{t+h}, \tag{27}$$

where h denotes the forecast horizons, $TR_t = (1-\phi_i)[\phi_\pi(\pi_t - \pi_t^*) + \phi_x(x_t - x_t^*)] + \phi_i(i_{t-1} - i_{t-1}^*)$ denotes the Taylor rule fundamentals, which is a combination of home and foreign inflation, output gap, and a one-period lag of the interest rate. Comparing TR_t with Eqs. (3) and (4), this specification implies that the policy parameters in the Taylor rules of the home and foreign countries are identical. Specifically, we follow Engel et al. (2007) to set $\phi_\pi = \phi_\pi^* = 1.5, \phi_x = \phi_x^* = 0.1, \phi_i = \phi_i^* = 0.9$.[14] Finally, ϵ_{t+h} is the error term of the predictive regression.

[14] We use TR_t here as a regressor, rather than use $\pi_t, \pi_t^*, x_t, x_t^*, i_{t-1}$ and i_{t-1}^* directly. The reason for using this setup is that our sample size is relatively small, and including too many regressors in the predictive regression may induce an efficiency loss when conducting long-horizon forecasts.

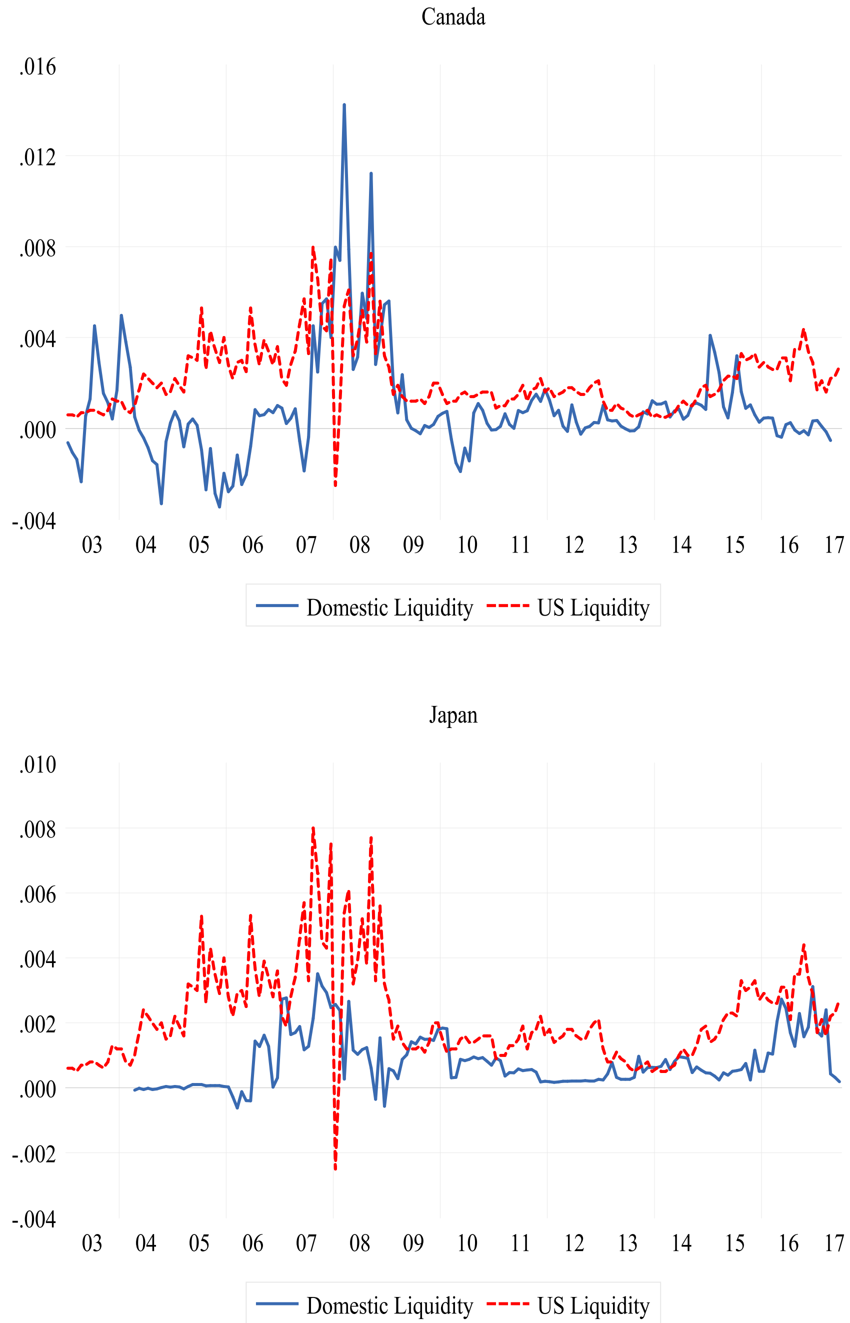

Fig. 4. Plots of the relative conventional measure of liquidity yield for home and foreign government bonds proposed by Nagel (2016): γ_t^{Nagel} and γ_t^{Nagel*}.

As shown in Engel and Wu (2023) and Rapach and Wohar (2006), there exist two potential econometric problems associated with Eq. (27). First, the overlapping observations of the dependent variable will generate serial correlation in the disturbance term when $h > 1$. Second, because the dependent variable $s_{t+h} - s_t = \Delta s_{t+1} + \Delta s_{t+2} + \cdots + \Delta s_{t+h}$, under the null of random walk forecasts (no change in exchange rate), $s_{t+h} - s_t$ can be very persistent when h is increased, and this will induce a serious size distortion when constructing the t-statistics. To deal with the first problem, we rely on Newey and West (1987)'s heteroscedasticity and serial correlation robust standard errors with a Bartlett kernel and lag truncation parameter of the nearest integer around $1.5h$. For the second problem, we make the inferences on the parameter estimates based on a bootstrap procedure.

Table 27
In-sample predictability: Using GC Repo–Treasury bill rate spread to measure liquidity yields.

In-sample results									
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	$\overline{R}^2$
Canada	-0.834***	0.472**	0.369**	-0.154	-0.195	-0.206	2.237**	1.192	0.113
(2003M2–2017M4)	(-3.130)	(2.189)	(2.073)	(-0.812)	(-0.723)	(-0.768)	(2.382)	(0.801)	
Japan	0.053	0.026	-0.199***	0.401	-2.027	-0.008	-5.659**	0.991	0.040
(2004M4–2017M6)	(0.217)	(0.133)	(-2.527)	(1.802)	(-1.336)	(-0.033)	(-2.008)	(0.409)	

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1}^{Tbill} + \theta_6 i_{t-1}^{Tbill*} + \theta_7\gamma_t^{Nagel} + \theta_8\gamma_t^{*Nagel}$ + regression errors. The numbers in parentheses are Newey-West corrected t-ratios. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

Table 28
Out-of-sample predictability comparison of models with random walk when using GC Repo-Treasury bill spread as proxy of liquidity yields: Rossi and Inoue (2012)'s sup-ENCNEW tests.

Out-of-sample results		
Home Currency	Compare (26) with driftless RW	Compare (26) with RW with a drift
k	9	8
Canada	20.119**	25.160***
Japan	12.718*	15.409**

Note: The predictive regression is $\Delta s_{t+1} = \theta_0 + \theta_1\pi_t + \theta_2\pi_t^* + \theta_3 x_t + \theta_4 x_t^* + \theta_5 i_{t-1}^{Tbill} + \theta_6 i_{t-1}^{Tbill*} + \theta_7\gamma_t^{Nagel} + \theta_8\gamma_t^{*Nagel}$ + regression errors. k denotes the difference between the number of regressors in the large (alternative) model and the small model (random walk). The critical values for re 11.226 (10%), 13.831 (5%) and 19.489 (1%) for $k = 8$, 11.888 (10%), 14.585 (5%), and 20.525 (1%) for $k = 9$, respectively. *, ** and *** indicate that the alternative model significantly outperforms the random walk model at the 10%, 5%, and 1% significance level, respectively.

We follow Rapach and Wohar (2006) and Kilian (1999) to implement the bootstrap procedure as follows. Our bootstrap sample of the nominal exchange rate is constructed under the null hypothesis of no predictability. The changes in the exchange rate follow a random walk with drift, and each of the independent variables (TR_t and η_t) follows an individual $AR(p)$ process. Specifically,

$$\Delta s_t = a_0 + e_t^s, \tag{28}$$

$$TR_t = b_0 + b_1 TR_{t-1} + \cdots + b_p TR_{t-p} + e_t^{TR}, \tag{29}$$

$$\eta_t = c_0 + c_1\eta_{t-1} + \cdots + c_p\eta_{t-p} + e_t^{\eta}, \tag{30}$$

where the disturbance vector $e_t = [e_t^s, e_t^{TR}, e_t^{\eta}]'$ is independently and identically distributed with covariance matrix Ω. We first estimate Eqs. (28)–(30) using ordinary least squares (OLS), where the lag order (p) in Eqs. (29) and (30) is selected using the Akaike Information Criterion (AIC) with a maximum lag length of 12 and compute the OLS residual vectors $\widehat{e}_t = [\widehat{e}_t^s, \widehat{e}_t^{TR}, \widehat{e}_t^{\eta}]'$, together with the OLS estimates $\widehat{a}_0, \widehat{b}_0, \widehat{b}_1, \cdots, \widehat{b}_p, \widehat{c}_0, \widehat{c}_1, \cdots, \widehat{c}_p$. We then randomly draw with replacement from $\widehat{e}_t$ to obtain an artificial series of disturbance vectors $\widehat{e}_t^*$, and use $\widehat{e}_t^*$ and the OLS estimates to generate an artificial sample of T observations from Eqs. (28)–(30). Note that the OLS residuals are drawn in tandem, and thus we preserve the contemporaneous correlation between the disturbances. We repeat this process 2000 times, providing an empirical distribution for the t-statistic corresponding to the coefficients in the long-horizon predictive regression in Eq. (27), and follow Engel and Wu (2023) to report the out-of-sample test statistics (CW test). For each statistic, the p-value is the proportion of the bootstrapped statistics that is greater than the statistic computed using the original sample. Note that CW is one-sided; a CW test statistic is significant at the 10% level if the p-value is less than or equal to 0.1. However, as the in-sample test is two-sided, the in-sample t-statistic is significant at the 10% level if the p-value is less than or equal to 0.05, or greater than or equal to 0.95 (see Rapach et al., 2005).

The bootstrap procedure described above can be applied to evaluate the long-horizon predictive power of τ_t, γ_t, and γ_t^* based on the long-horizon predictive regression as follows:

$$s_{t+h} - s_t = \theta_0^h + \theta_{TR}^h TR_t + \theta_\tau^h \tau_t + \theta_\gamma^h \gamma_t + \theta_{\gamma^*}^h \gamma_t^* + \epsilon_{t+h}. \tag{31}$$

By assuming τ_t, γ_t, and γ_t^* follow AR(p) processes, we can compute the bootstrap p-values of the in-sample t-statistics and out-of-sample CW test statistics based on Eq. (31).

Tables 29 and 30 report the estimates of Eqs. (27) and (31), respectively. As our data span is relatively short (typically from 1998 to 2018), we set the longest horizon as 24 months. To save space, we report the parameter estimates, t-statistics, bootstrap p-values of θ_η^h,

Table 29
In-sample long-horizon predictability of liquidity yield: Estimation results of (27).

Long-Horizon Regression Estimation Results			
Home Country	θ_{η}^{6} **($h = 6$)**	θ_{η}^{12} **($h = 12$)**	θ_{η}^{24}**($h = 24$)**
Australia	13.581**	15.694	32.809**
t-stat	(2.902)	(2.013)	(3.776)
p-value	(0.009)	(0.064)	(0.009)
$\overline{R}^2$	[0.005]	[0.078]	[0.142]
Canada	3.648	9.399	16.252
t-stat	(0.852)	(1.309)	(1.603)
p-value	(0.274)	(0.183)	(0.206)
$\overline{R}^2$	[0.002]	[0.054]	[0.189]
Denmark	0.091	0.322	0.731
t-stat	(0.044)	(0.074)	(0.115)
p-value	(0.971)	(0.963)	(0.938)
$\overline{R}^2$	[0.033]	[0.067]	[0.220]
Euro Area	1.602	9.130	14.288
t-stat	(0.317)	(0.946)	(0.838)
p-value	(0.807)	(0.514)	0.613)
$\overline{R}^2$	0.013	[0.044]	[0.197]
Japan	2.054	5.943	6.514
t-stat	(0.686)	(1.001)	(0.787)
p-value	(0.325)	(0.241)	(0.314)
$\overline{R}^2$	[0.036]	[0.204]	[0.021]
New Zealand	6.031	8.555	17.310
t-stat	(1.411)	(1.189)	(2.534)
p-value	(0.126)	(0.209)	(0.067)
$\overline{R}^2$	[0.013]	[0.131]	[0.163]
Norway	-0.782	-1.618	-1.664
t-stat	(-1.396)	(-1.589)	(-1.815)
p-value	(0.842)	(0.859)	(0.857)
$\overline{R}^2$	[0.065]	[0.123]	[0.050]
Sweden	3.613	6.617	15.992
t-stat	(1.128)	(1.012)	(1.812)
p-value	(0.210)	(0.271)	(0.170)
$\overline{R}^2$	[0.034]	[0.036]	[0.041]
Switzerland	0.021	-5.535	-0.172
t-stat	(0.008)	(-2.155)	(-0.036)
p-value	(0.513)	(0.950)	(0.538)
$\overline{R}^2$	[0.003]	[0.234]	[0.053]
UK	4.621	9.500*	13.481
t-stat	(1.497)	(2.633)	(1.688)
p-value	(0.139)	(0.039)	(0.176)
$\overline{R}^2$	[0.044]	[0.007]	[0.027]

Note: The long-horizon regression is $s_{t+h} - s_t = \theta^h + \theta_{TR}^h TR_t + \theta_{\eta}^h \eta_t + \epsilon_{t+h}$. The numbers in parentheses are Newey-West corrected t-ratios, and bootstrapped p-values, and the numbers in brackets are adjusted R^2 values. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

$\theta_{\tau}^h, \theta_{\gamma}^h$, and $\theta_{\gamma^*}^h$ at $h = 6, 12$, and 24 to highlight the predictive content of liquidity yields. An adjusted R^2 for each long-horizon predictive regression is also reported.

In Table 29, the in-sample predictive power of η_t typically disappears at longer horizons for all the countries we considered except Australia. Similarly, the long-horizon predictive power of γ_t for the exchange rate can only be found in Australia, Sweden, and the UK at $h = 6$. For the other sample countries and forecasting horizons, they are not statistically significant in general, suggesting that the liquidity yields do not exhibit long-horizon predictive power for nominal exchange rates when using in-sample predictive tests.

A similar conclusion can also be found in out-of-sample tests. Tables 31 and 32 report the CW test statistics and associated bootstrap p-values based on Eqs. (27) and (31), respectively. We find that Eq. (27) exhibits out-of-sample predictive power at $h = 6$ in the Euro Area, Japan, and the UK, while Eq. (31) exhibits out-of-sample predictive power in Canada, the Euro Area, and the UK. In sum, liquidity yield exhibits out-of-sample long-horizon predictive power for only three of the 10 countries we considered, which suggests that the long-horizon predictions of nominal exchange rates based on liquidity yields do not enjoy strong empirical support.[15]

[15] We do not report the sup-ENCNEW test results because they are also insignificant in general. This is consistent with the empirical exercise in Rossi (2013) in which the sup-ENCNEW test finds no long-horizon predictive power on exchange rate movements.

Table 30
In-sample long-horizon predictability of liquidity yield: Estimation results of (31).

Long-Horizon Regression Estimation Results									
Home Country	θ^6_τ $(h=6)$	θ^6_γ $(h=6)$	$\theta^6_{\gamma^*}(h=6)$	θ^{12}_τ $(h=12)$	θ^{12}_γ $(h=12)$	$\theta^{24}_{\gamma^*}(h=12)$	θ^{24}_τ $(h=24)$	θ^{24}_γ $(h=24)$	$\theta^{24}_{\gamma*}(h=24)$
Australia	6.364	32.973*	-19.609	1.513	44.979*	-30.789	16.432	54.726**	-55.433
t-stat	(1.579)	(2.702)	(-2.220)	(0.164)	(3.122)	(-2.491)	(1.281)	(5.024)	(-6.661)
p-value	(0.087)	(0.029)	(0.929)	(0.402)	(0.030)	(0.926)	(0.173)	(0.006)	(0.997)
$\overline{R}^2$	[0.026]	#	#	[0.332]	#	#	[0.096]	#	#
Canada	8.822	13.563	1.360	11.415	23.673	-3.489	8.353	27.510	-13.276
t-stat	(2.169)	(2.028)	(0.309)	(1.491)	(2.003)	(-0.485)	(0.651)	(1.546)	(-1.413)
p-value	(0.057)	(0.083)	(0.408)	(0.185)	(0.099)	(0.634)	(0.398)	(0.196)	(0.792)
$\overline{R}^2$	[0.018]	#	#	[0.138]	#	#	[0.097]	#	#
Denmark	4.854	9.997	1.175	7.042	15.975	-0.038	13.426	33.966	-3.046
t-stat	(1.936)	(2.044)	(0.262)	(1.953)	(2.420)	(-0.006)	(2.504)	(3.206)	(-0.355)
p-value	(0.117)	(0.063)	(0.379)	(0.130)	(0.062)	(0.470)	(0.213)	(0.071)	(0.424)
$\overline{R}^2$	[0.078]	#	#	[0.173]	#	#	[0.386]	#	#
Euro Area	4.996	11.510	-6.192	23.696	37.395	-19.318	41.141	75.537	-39.970
t-stat	(0.560)	(1.055)	(-1.099)	(1.875)	(2.481)	(-2.397)	(3.803)	(3.227)	(-2.815)
p-value	(0.450)	(0.251)	(0.759)	(0.191)	(0.070)	(0.916)	(0.067)	(0.070)	(0.913)
$\overline{R}^2$	[0.184]	#	#	[0.159]	#	#	[0.161]	#	#
Japan	-1.317	-16.399	-0.443	0.968	-30.458	-0.624	-6.215	-54.402	-2.277
t-stat	(-0.341)	(-1.892)	(-0.140)	(0.142)	(-2.046)	(-0.123)	(-0.605)	(-2.089)	(-0.439)
p-value	(0.631)	(0.937)	(0.532)	(0.505)	(0.910)	(0.529)	(0.653)	(0.893)	(0.604)
$\overline{R}^2$	[0.147]	#	#	[0.060]	#	#	[0.268]	#	#
New Zealand	2.331	7.228	3.614	1.228	10.416	3.079	19.609	17.032	-16.520
t-stat	(0.472)	(1.418)	(0.437)	(0.121)	(1.255)	(0.234)	(1.100)	(2.259)	(-1.534)
p-value	(0.276)	(0.187)	(0.338)	(0.383)	(0.240)	(0.387)	(0.181)	(0.139)	(0.769)
$\overline{R}^2$	[0.081]	#	#	[0.089]	#	#	[0.321]	#	#
Norway	-0.989	-16.445	-0.578	4.157	-29.067	-0.642	-13.559	-69.492	-1.642
t-stat	(-0.223)	(-1.840)	(-0.184)	(0.449)	(-1.909)	(-0.132)	(-0.998)	(-2.250)	(-0.328)
p-value	(0.573)	(0.923)	(0.545)	(0.414)	(0.906)	(0.525)	(0.727)	(0.883)	(0.576)
$\overline{R}^2$	[0.196]	#	#	[0.069]	#	#	[0.321]	#	#
Sweden	0.156	5.771	5.038	0.341	9.412	3.110	0.319	15.775	-8.041
t-stat	(0.257)	(1.250)	(0.873)	(0.321)	(1.586)	(0.350)	(0.171)	(1.557)	(-1.299)
p-value	(0.543)	(0.167)	(0.217)	(0.518)	(0.143)	(0.365)	(0.584)	(0.188)	(0.749)
$\overline{R}^2$	[0.163]	#	#	[0.108]	#	#	[0.273]	#	#
Switzerland	-0.830	5.189*	-0.799	-2.479	-3.699	1.415*	-4.966	6.514	-1.545
t-stat	(-1.379)	(2.138)	(-0.185)	(-2.425)	(-1.687)	(1.782)	(-2.575)	(1.929)	(-0.178)
p-value	(0.823)	(0.080)	(0.515)	(0.926)	(0.896)	(0.090)	(0.894)	(0.161)	(0.483)
$\overline{R}^2$	[0.072]	#	#	[0.174]	#	#	[0.176]	#	#
UK	7.800	8.478**	2.566	7.722	19.610**	-3.048	14.524	22.504	-4.708
t-stat	(1.766)	(3.433)	(0.479)	(1.703)	(3.564)	(-0.370)	(1.345)	(2.375)	(-0.466)
p-value	(0.112)	(0.012)	(0.310)	(0.153)	(0.014)	(0.583)	(0.256)	(0.085)	(0.579)
$\overline{R}^2$	[0.039]	#	#	[0.127]	#	#	[0.056]	#	#

Note: The long-horizon regression is $s_{t+h} - s_t = \theta^h + \theta^h_{TR} TR_t + \theta^h_\tau \tau_t + \theta^h_\gamma \gamma_t + \theta^h_{\gamma^*} \gamma^*_t + \epsilon_{t+h}$. The numbers in parentheses are Newey-West corrected *t*-ratios, and bootstrapped *p*-values, and the numbers in brackets are adjusted R^2 values. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

We argue that the absence of long-horizon predictive power of liquidity yields can be attributed to how we model the candidate predictors and their statistical properties, as shown by Engel and Wu (2023) and Kilian (1999); for example, how the predictors are modeled under the null hypothesis of no predictability, and whether they are cointegrated with the exchange rate. It is of interest to examine how the results of the forecasting exercise would be altered under different specifications of the predictors; however, this is beyond the scope of this paper and we defer this to future research.

7. Conclusion

In this paper, we use the pricing condition of the liquidity yield of government bonds proposed by Jiang et al. (2018), together with the Taylor rule of the home and foreign countries to derive an empirical model with Taylor rule fundamentals and liquidity yield of domestic government bonds relative to foreign bonds. We then use the predictive regression implied by the model to perform both in-sample and out-of-sample forecasting exercises to assess the short-run predictive power of the liquidity yield on one-month-ahead exchange rate movements. Using monthly exchange rate data of the Australian dollar, Canadian dollar, Danish krone, the euro, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, Swiss franc, and the UK pound against the US dollar, we elucidate the predictive content of the liquidity yield for future exchange rate movements. The model predicts exchange rates significantly in

Table 31
Out-of-sample test of long-horizon predictability: Results of Eq. (27).

	CW test results					
Home Country	$h=6$		$h=12$		$h=24$	
	Compare with a driftless RW	Compare with RW with a drift	Compare with a driftless RW	Compare with RW with a drift	Compare with a driftless RW	Compare with RW with a drift
Australia	−1.438	−0.254	2.002	3.086	3.269	9.597*
p-value	(0.487)	(0.390)	(0.203)	(0.189)	(0.211)	(0.090)
Canada	-2.045	0.627	-2.128	3.661	-6.775	0.288
p-value	(0.544)	(0.265)	(0.504)	(0.170)	(0.914)	(0.288)
Denmark	-2.532	-0.644	-3.090	2.132	-5.845	-3.357
p-value	(0.623)	(0.387)	(0.616)	(0.208)	(0.840)	(0.664)
Euro Area	1.136	5.163*	-0.075	6.221	0.750	15.356**
p-value	(0.229)	(0.078)	(0.344)	(0.107)	(0.336)	(0.038)
Japan	4.567	9.104**	-0.996	1.045	-2.597	1.771
p-value	(0.102)	(0.046)	(0.467)	(0.288)	(0.499)	(0.311)
New Zealand	4.592*	-1.675	4.998	-0.510	-0.596	2.014
p-value	(0.086)	(0.665)	(0.113)	(0.442)	(0.402)	(0.248)
Norway	-2.151	-1.627	-0.965	-0.243	3.191	2.032
p-value	(0.598)	(0.605)	(0.385)	(0.404)	(0.173)	(0.248)
Sweden	-2.321	-0.573	-2.359	0.653	-0.449	-1.772
p-value	(0.603)	(0.402)	(0.534)	(0.326)	(0.348)	(0.518)
Switzerland	-1.327	-2.305	-0.746	-2.337	-1.144	-2.933
p-value	(0.459)	(0.684)	(0.371)	(0.603)	(0.419)	(0.652)
UK	10.776**	15.120**	-0.287	8.638*	-2.656	1.318
p-value	(0.029)	(0.018)	(0.318)	(0.074)	(0.538)	(0.324)

Note: The numbers in parentheses are bootstrapped *p*-values. Superscripts *, **, and *** indicate a significance at 10% level, 5% level and 1% level, respectively.

Table 32
Out-of-sample test of long-horizon predictability: Results of Eq. (31).

	CW test results					
Home Country	$h=6$		$h=12$		$h=24$	
	Compare with a driftless RW	Compare with RW with a drift	Compare with a driftless RW	Compare with RW with a drift	Compare with a driftless RW	Compare with RW with a drift
Australia	-3.353	-3.503	1.363	0.597	0.509	4.642
p-value	(0.780)	(0.850)	(0.257)	(0.328)	(0.347)	(0.214)
Canada	25.373***	25.804***	0.416	2.828	2.110	1.401
p-value	(0.009)	(0.007)	(0.283)	(0.203)	(0.239)	(0.310)
Denmark	-4.303	-3.707	-1.865	3.061	-5.662	-0.766
p-value	(0.861)	(0.822)	(0.461)	(0.226)	(0.798)	(0.449)
Euro Area	4.782	7.461*	3.258	7.665*	-0.609	3.005
p-value	(0.106)	(0.070)	(0.177)	(0.099)	(0.427)	(0.280)
Japan	-1.510	-0.999	-4.712	-4.064	-3.463	-1.738
p-value	(0.459)	(0.448)	(0.767)	(0.760)	(0.576)	(0.525)
New Zealand	3.664	1.395	2.799	6.160	23.493**	-4.140
p-value	(0.153)	(0.241)	(0.202)	(0.124)	(0.029)	(0.789)
Norway	0.949	5.766	5.305	5.002	-2.835	32.568**
p-value	(0.245)	(0.106)	(0.125)	(0.161)	(0.590)	(0.016)
Sweden	-0.095	−0.879	-3.188	1.265	-2.806	3.871
p-value	(0.302)	(0.394)	(0.575)	(0.296)	(0.510)	(0.238)
Switzerland	-2.566	-2.664	0.032	-1.220	-1.335	-1.871
p-value	(0.625)	(0.687)	(0.307)	(0.450)	(0.415)	(0.509)
UK	4.189	6.651*	0.577	2.909	-1.404	0.614
p-value	(0.127)	(0.086)	(0.296)	(0.217)	(0.424)	(0.367)

Note: The numbers in parentheses are bootstrapped *p*-values. Superscripts *, **, and *** indicate a significance at the 10% level, 5% level and 1% level, respectively.

seven out of 10 currencies using out-of-sample tests. Moreover, when controlling the currency swap market frictions, the model with the liquidity yield suggests that the inclusion of a measure of domestic government liquidity is essential, and exhibits in-sample and out-of-sample predictive power.

Our results corroborate the empirical findings in Engel and Wu (2022) that the government liquidity yield is essential in exchange rate determination, and help to demystify the Meese–Rogoff puzzle. In particular, our empirical results show that the forecasting performance of a successful predictive model of exchange rates, i.e., the Taylor rule model, can be further improved by incorporating the liquidity yield as an additional predictor.

CRediT authorship contribution statement

Shiu-Sheng Chen: Data, Writing-reviewing and editing. **Yu-Hsi Chou:** Writing–original and revised draft preparation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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