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# Forward-Looking Policy Rules and Currency Premia

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## Abstract

We evaluate the cross-sectional predictive ability of a forward-looking monetary policy reaction function, or Taylor rule, in both statistical and economic terms. We find that investors require a premium for holding currency portfolios with high implied interest rates while currency portfolios with low implied rates offer negative currency excess returns. Our forward-looking Taylor rule signals are orthogonal to current nominal interest rates and disconnected from carry trade portfolios and other currency investment strategies. The profitability of the Taylor rule portfolio spread is mainly driven by inflation forecasts rather than the output gap and is robust to data snooping and a wide range of robustness checks.

## I. Introduction

In this article, we assess the economic value of forward-looking Taylor rules for generating currency excess returns. Taylor rules, originally proposed by Henderson and McKibbin (1993) and Taylor (1993), emerged during the 1990s as a proposed family of orthodox monetary policy rules by which inflation-targeting central banks can, in principle, infer the appropriate level of the policy interest rate conditional on the inflation rate, output gap (the gap between actual and potential national output) and an inflation target (Bernanke, Laubach, Mishkin, and Posen (1999)), so that, for example, a tightening of monetary policy is implied (a rise in the policy interest rate) when the inflation rate exceeds its policy target, conditional on the level of the output gap (so that the interest rate raise may be attenuated when national output is deemed to be below its potential level, for example). Although in practice, no national central bank has explicitly adopted a Taylor rule, such a rule may serve as a concise descriptive proxy for central bank policy, and there is long-standing literature that documents the success of Taylor rule models in capturing movements in interest rates for a number of countries (e.g., Clarida,

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Galí, and Gertler (1998), Bernanke, Laubach, Mishkin, and Posen (1999), and Bernanke (2015)).[1]

There is much smaller literature (e.g., Clarida and Waldman (2008), Molodtsova and Papell (2009)) that has sought to predict foreign exchange rate movements based on Taylor rule models: the underlying rationale here is that in a world of relatively low inflation differentials and inflation targeting by central banks, if inflation is forecast to exceed the central bank's inflation target, this is likely to trigger an interest rate hike (according to the Taylor rule) which, for a given level of foreign interest rates, will make interest-bearing assets denominated in that currency relatively more attractive to investors and therefore lead to an appreciation of its external value. Although uncovered interest parity would suggest that exchange rate changes will eliminate the profitability of arbitraging cross-country differences in interest rates, empirical studies have in fact documented that such trading strategies consistently generate substantial profits (e.g., Menkhoff, Sarno, Schmeling, and Schrimpf (2012)), mainly because high-interest-rate currencies tend to appreciate rather than depreciate against low-interest-rate currencies. (This phenomenon is often referred to as the "forward-premium puzzle," since it is a prima facie violation of the simple (risk-neutral) efficient markets hypothesis (Fama (1984)).) Combining this with a similar Taylor rule model for the foreign country suggests that, insofar as Taylor rules may be used to predict relative interest rate differentials between countries, they should be useful for predicting movements in the foreign exchange rates between countries. Clarida and Waldman (2008) found evidence supporting this proposition by examining the sign and significance of the correlation between inflation surprises and nominal exchange rate changes, while Molodtsova and Papell (2009) found evidence that a forecasting model based on Taylor rule fundamentals was, at least at some forecast horizons, able to outperform various standard benchmark models such as a random walk (no change) model in terms of mean forecast error on a country-by-country or time-series basis.[2]

In the present study, we focus on the cross-sectional portfolio analysis of relative exchange rate movements in order to examine whether Taylor rules can be used to generate meaningful trading signals that generate significant excess portfolio returns, paying careful attention to the information sets that would have been available to traders at each point in time. This analysis follows recent studies in the literature which investigate the cross-sectional variation of country characteristics and their implications for exchange rate movements (e.g., Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012), (2016),

[1]The view of the Taylor rule as a descriptive rather than prescriptive tool is emphasized by a former Chair of the Board of Governors of the U.S. Federal Reserve System, Bernanke (2015), who argues against the use of an explicit Taylor rule ("The simplicity of the Taylor rule disguises the complexity of the underlying judgments that [policy makers] must continuously make if they are to make good policy decisions"), but nevertheless demonstrates empirically that "U.S. monetary policy since the early 1990s is pretty well described by a modified Taylor rule." In the present application, the descriptive (and hence predictive) role of the Taylor rule is the object of our analysis.

[2]In related work, Filippou, Rapach, Taylor, and Zhou (2020) and Filippou and Taylor (2017) find that inflation and unemployment are important predictors of exchange rates.

Lettau, Maggiori, and Weber (2014), Filippou, Gozluklu, and Taylor (2018), and Verdelhan (2018)). In terms of accurately capturing the information set of traders, we employ survey data on exchange rate expectations in our analysis and investigate the use of revised and unrevised data sets for inflation and the output gap and a range of different measures of the output gap.[3] To the best of the present authors' knowledge, this is also the first study to investigate the cross-sectional predictive power of forward-looking Taylor rule models for currency portfolio returns.

Using a cross-sectional portfolio approach with our forward-looking Taylor rule to imply future interest rate movements, we show that a spread portfolio that buys high-implied interest rate portfolios and sells low-implied interest rate portfolios renders positive and highly significant currency excess returns that are statistically significant and economically meaningful in terms of various investment performance measures: this strategy offers high and statistically significant annualized excess returns and Sharpe ratios and is highly profitable even after considering implementation costs. The performance of the strategy is also robust to different measures of the output gap, and the Taylor rule portfolios exhibit very low correlations with other currency investment strategies or equity strategies. In particular, the correlation of the strategy with currency carry trades is very low by construction as the Taylor rule signal is orthogonalized with respect to nominal interest rates. In addition, our Taylor rule factor offers a low correlation with the output gap factor of Colacito, Riddiough, and Sarno (2020), because its profitability is mainly driven by the deviation of expected inflation from its target. We also show that our Taylor rule factors are not correlated with inflation factors (e.g., Dahlquist and Hasseltoft (2020)). Furthermore, we find very low correlation of the signal with existing uncertainty measures. We also find that the payoffs of the strategy remain highly significant in economic and statistical terms when we use different vintages of revised and unrevised data, as they are when we construct a dynamic forward-looking Taylor rule model where the coefficients of inflation and the output gap are estimated dynamically based on a constrained linear regression model using a 36-month rolling window. In addition, we investigate competing explanations regarding the profitability of our forward-looking Taylor rule trading signal on the basis of unmodeled risk and data-snooping (White (2000)). To this end, we examine the pricing ability of other factors such as carry trade, momentum, value, output gap, and inflation factors for Taylor rule-sorted portfolios, and find that these factors are not able to explain the cross-sectional variation of the Taylor rule test assets. We find that a forward-looking Taylor rule spread portfolio demonstrates strong pricing ability for the cross-section of Taylor rule-sorted portfolios as it serves as a slope factor, and shows that the Taylor rule spread portfolio is also priced in the cross-section of currency portfolios that include carry trade, momentum, value, output gap, inflation and Taylor rule portfolios, yielding relatively high generalized least squares (GLS) $R^2$ and demonstrating strong performance in terms of goodness of fit. In this way we guard against the possibility of a "lucky factor" that is typically

[3]This analysis accords with Bernanke (2015): "The Taylor rule assumes that policymakers know, and can agree on, the size of the output gap. In fact, as current debates about the amount of slack in the labor market attest, measuring the output gap is very difficult."

observed in portfolios with strong factor structure (e.g., Lewellen, Nagel, and Shanken (2010)).

We also consider the pricing ability of other risk factors that demonstrate strong cross-sectional power for currency returns, namely, global exchange rate volatility, global exchange rate illiquidity, global risk aversion, and global political risk, and show that only global political risk provides weak pricing power for the cross-section of Taylor-rule sorted portfolios. In addition, we examine the implications of the Taylor rule portfolio for other currency investment strategies such as carry trades, momentum, and fundamental value, and we find that the Taylor rule spread portfolios is a strong predictor of the cross-section of currency carry trades and currency momentum portfolios but the does not offer any information for other currency strategies.

Our study also relates the cross-sectional predictive power of forward-looking with backward-looking (using lagged inflation) Taylor rule models using vintage data for both inflation and output. One could think of the backward-looking model as a special version of the forward-looking model if lagged inflation or linear combinations of lagged inflation could serve as adequate proxies of future inflation (e.g., Clarida et al. (2000)). We find that such portfolios also offer positive and significant returns but they are less profitable in comparison to forward-looking Taylor rule models. In addition, the forward-looking models prove highly positive and statistically significant even after controlling for backward-looking Taylor rule portfolios or carry trade portfolios, indicating that they offer information over and above those factors.

Our results are robust to a large number of robustness checks. In particular, we show that the returns of the strategy and the performance measures are not subject to data snooping. To this end, we perform White's (2000) reality check, using the stationary bootstrap of Politis and Romano (1994), and reject the null hypothesis of underperformance at any standard significance level even after controlling for transaction costs. In addition, we employ different methods of estimating the trend component of output such as the Hodrick and Prescott (1980), (1997) filter, the Baxter and King (1999) filter, the linear projection of Hamilton (2018), and a quadratic time trend (e.g., Clarida et al. (1998), Orphanides and Norden (2002)), and find qualitatively identical and quantitatively similar results. We also consider the robustness of our results across various subsamples of the data set, as well as consider trading rule returns from the perspective of non-U.S.-based investors and include inflation forecasts of different vintages. In every case, we find that our results are qualitatively robust to different specification tests and offer positive and significant returns.

Since we demonstrate that our results are robust to data snooping tests, the profitability of forward-looking Taylor rule strategies could possibly stem from either risk or mispricing, or both. We do not find evidence of mispricing. On the other hand, we show that the forward-looking Taylor rule factor loadings exhibit strong predictability for currency returns, consistent with investors requiring a risk premium for holding currencies with high implied interest rates while currencies with low implied interest rates offer lower returns as they provide a hedge in the bad state of the world when high implied interest rate currencies drop in value.

The remainder of the article is set out as follows: Section II discusses the forward-looking Taylor rule model and Section III offers a data description. Section IV provides our empirical results. Section V presents our robustness checks and Section VI concludes.

## II. A Forward-Looking Taylor Rule Model

In this section, we analyze the implications of a forward-looking Taylor rule model over a historical multi-country data set spanning several decades. In particular, we develop a trading signal which is based on a weighted average of the standard deviation of expected inflation from a target level, a measure of the output gap, and the current nominal interest rate. Intuitively, in an environment with relatively low inflation differentials and explicit inflation targeting by many central banks at least until 2008 (i.e., the recent financial crisis) (Bernanke et al. (1999)), if inflation is forecast to exceed the central bank's inflation target, this would likely trigger an interest rate increase. This effect would attract carry trade investment leading to an appreciation of the home currency.[4] To this end, we propose a Taylor rule signal that captures the surprise element of inflation (e.g., the difference between an inflation forecast and the associated target of the central bank). We consider a measure that is orthogonal to interest rates so as to examine the cross-sectional predictive ability of the monetary policy rule beyond current carry trade profitability. In other words, our main goal is to capture the information content of a forward-looking Taylor rule model over and above the one implied by the realized change in the interest rate differential (e.g., a risk premium associated with the carry trade strategy). In one sense, therefore, our Taylor rule signal captures expected future carry trade profitability orthogonalized with respect to current carry trade profitability.

Monetary policy rules of this kind were originally proposed by Henderson and McKibbin (1993) and Taylor (1993), who define the implicit interest rate based on deviations of *past* inflation from its target and also as an indicator of the size of the output gap. Clarida, Galí, and Gertler (2000), among others, propose a forward-looking Taylor rule as an optimal monetary policy rule which takes the following form:

$$r_t^* = \bar{r} + \bar{\beta}\left(\pi_t^f - \pi_t^*\right) + \bar{\gamma} x_t, \tag{1}$$

where $r_t^*$ denotes the implied appropriate policy level of the short-term interest rate, $\bar{r}$ denotes the long-run equilibrium nominal rate, $\pi_t^f$ is the forecast of inflation made at time $t$ for $n$ periods ahead, $\pi_t^*$ denotes the inflation target, denotes the output gap and the parameters $\bar{\beta}$ and $\bar{\gamma}$ are expected to be positive.[5] In addition, it is standard in empirical studies of Taylor rules to introduce an interest rate smoothing function, whereby the interest rate adjusts each period only by a fraction of the distance

[4]For example, the increase of UK gilts in Nov. 2017 due to higher inflation resulted in an appreciation of the British pound during that period.

[5]We have denoted the inflation target with a time subscript to emphasize the fact that this may change over time, although in practice it will tend to be largely static. The slope parameters are denoted with a bar in (1) for ease of notation and consistency in moving from (3) to (4).

between the desired rate $r_t^*$ and the actual rate $r_t$. This can be interpreted as capturing the monetary authorities' reluctance to generate large jumps in interest rates but can also be interpreted as the markets slowly absorbing the implied Taylor rule information into market interest rates. It takes the form:

$$r_{t+1} - r_t = \lambda\left(r_t^* - r_t\right), 0 < \lambda < 1. \tag{2}$$

Combining (1) and (2):

$$r_{t+1} - r_t = \lambda\bar{r} + \lambda\bar{\beta}\left(\pi_t^f - \pi_t^*\right) + \lambda\bar{\gamma}x_t - \lambda r_t. \tag{3}$$

Equation (3) is the core insight of the trading signal: If a Taylor rule broadly captures the stance of monetary policy, then a weighted average of the inflation gap and the output gap, adjusted for the component already priced into the interest rates, should be a good predictor of the change in interest rates. Thus, the expectation is that an interest rate increase will, other things equal, make a currency relatively more attractive, implying that an effective currency signal can be based on the right-hand side of the equation (3). Thus, equation (3) implies the "raw trading signal":

$$\xi_t = \beta\left(\pi_t^f - \pi_t^*\right) + \gamma x_t - \lambda r_t. \tag{4}$$

The signal can be thought of as raw as expressed in (4) in that it applies only to a single exchange rate and needs to be put into a portfolio context and further refined into a trading strategy, as discussed below. The signal requires a measure of the output gap, which is unobserved, and our first estimate of this is based on the procedure of Hodrick and Prescott (HP) (1980). Specifically, we decompose the output into trend and cyclical components using the HP filter, and our empirical proxy of the output gap is detrended industrial production ($y_t^{\text{gap}}$), representing short-term deviations of the output (i.e., cyclical component) from the economy's potential growth path (i.e., trend component). We also use an alternative measure of the output gap based on unemployment: the unemployment gap ($u_t^{\text{gap}}$) is measured as the deviation of unemployment ($u_t$) from its natural rate which is proxied by an HP filter trend variable ($u_t^*$). Thus, we measure the output gap in (4) alternatively as $x_t = y_t^{\text{gap}}$ or $x_t = -u_t^{\text{gap}}$.[6]

It is straightforward to demonstrate that the Taylor rule will only be stabilizing if the slope coefficient on expected inflation is greater than unity as this implies an increase in the real interest rate if inflation is above target, other things equal. Similarly, the policy rule will only be stabilizing economic activity if the slope coefficient on the output gap is positive. Here, we consider $\beta = 1.5$ consistently with the literature and $\gamma = 0.50$.[7] Our estimate of $\lambda$ is determined dynamically, based on a

[6]Note that the forward-looking Taylor rule includes *expected* inflation but the *current* output gap. The expected output gap would be inappropriate for two reasons. First, macroeconomic theory suggests that the current output gap will lead to inflation, for example, through an expectations-augmented Phillips curve. Second, the Taylor rule could not function as a stable control rule in an expectations-consistent macro model if all of its state variables were forward-looking.

[7]Later, we consider different values of the coefficients as well as dynamic values based on rolling regressions.

cross-sectional (i.e., across countries) regression of $1.5\left(\pi_t^f - \pi_t^*\right) + 0.5x_t$ onto the interest rate at every time period $t$ in order to control for carry trade profitability.

The link from expected movements in interest rates to exchange rates via carry trades is relatively uncontroversial. Note, however, that the overall rationale of the signal is conditioned on the assumption of relatively low and stable inflation, so that any deviations from purchasing power parity are deemed relatively unimportant. In such a world, small rises in (forecast) inflation will not have their traditional impact on the exchange rate of generating a depreciation (because of relative purchasing power parity) as the expected impact on expected interest rates is, via the carry trade, a stronger influence on exchange rate movements.[8]

## III. Data and Portfolio Construction

This section offers a detailed description of the exchange rate data, the revised, vintage data, and the corresponding forecasts of inflation. In addition, we provide a detailed analysis of our portfolio construction based on the forward-looking Taylor rule signal.

### A. Exchange Rate Data

We collect daily spot and forward exchange rates from Barclays and Reuters via Datastream. We focus our analysis on 20 currencies against the U.S. dollar. Our data span the period Jan. 1990 to Mar. 2017.[9] We create end-of-month series of daily spot and 1-month forward rates (e.g., as in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011)). Thus, our data set is not averaged over each month but consists of spot and forward rates on the last trading day of each month. Our sample comprises the following 20 countries: Australia, Brazil, Canada, Czech Republic, Europe,

[8]The conjecture that purchasing power parity will be dominated by expected carry trade investments when inflation rates are relatively low and stable is supported by research on nonlinearities in the exchange rate-inflation nexus. In particular, research on nonlinearity in exchange rate adjustment suggests that, although there is evidence that PPP holds on average over long periods of time and during relatively high inflation episodes (Taylor and McMahon (1988), Flood and Taylor (1996), and Lothian and Taylor (1996)), the strength of the attraction toward PPP for an exchange rate may depend nonlinearly upon the level of inflation in each of the countries concerned and the relative inflation differential. The argument here is straightforward: when the inflation differential is high, failure of the nominal exchange rate to correct for the differential (i.e., for the high-inflation currency to depreciate) will lead to large deviations from "fair" (PPP equilibrium) value that will then tend to mean revert relatively quickly, for example, because there is increased scope for goods arbitrage (Taylor, Peel, and Sarno (2001)), or because there is a higher degree of consensus concerning directional forecasts from currency advisors when the exchange rate is more strongly misaligned (Kilian and Taylor (2003)), or else because there is an increased probability of official intervention (Taylor (2004)). Conversely, when the inflation differential is relatively small, failure of the nominal exchange rate to correct for the differential will lead to relatively small deviations from fair value that will tend to persist because there is less scope for profitable goods arbitrage, less degree of consensus among exchange rate advisors concerning directional forecasts, and less risk of official intervention.

[9]Our time series and cross-section of de jure or de facto inflation-targeting countries are determined by the availability of the inflation forecast data. For example, our inflation forecast data starts in Jan. 1990. This date coincides with the implementation of Taylor rule models by a large number of major central banks (Bernanke et al. (1999)).

Germany, Hungary, Indonesia, Japan, South Korea, Mexico, New Zealand, Norway, Philippines, Poland, Spain, Sweden, Switzerland, Thailand, and United Kingdom.

## B. Sample Filters

The Euro Area countries are excluded after the introduction of the euro in Jan. 1999. However, some countries entered the Euro Zone later than Jan. 1999; in this case, their exchange rates are excluded from the sample at the date of entry. Those currencies that were partly or completely pegged to the U.S. dollar are not excluded from the sample because their forward foreign exchange contracts were available to investors.

## C. Currency Excess Returns

We define $S_t$ ($F_t$) as the level of the spot (1-month forward) rate at time $t$. Each currency is expressed in units of foreign currency per U.S. dollar so that an appreciation of the foreign currency relative to the dollar is associated with a decrease in $S_t$. We denote by $\mathrm{RX}_{t+1}$ the payoff of a strategy that buys a foreign currency in the forward market at time $t$ and goes short the foreign currency in the spot market the following month (e.g., at time $t+1$). Thus, the currency excess return is expressed as:

$$\mathrm{RX}_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}.$$

Expressed in this fashion, the currency excess return can be seen to consist of two components, namely, the forward discount and the exchange rate return. The forward discount serves as a good proxy for the interest rate differential, that is, $\frac{F_t - S_t}{S_t} \approx r_t - r_t^{\mathrm{US}}$, where $r_t$ $\left(r_t^{\mathrm{US}}\right)$ denotes the foreign (domestic) riskless nominal interest rate of the foreign country, under the assumption that covered interest-rate parity (CIP) holds.[10] The latter implies that the excess return can be expressed as $\left(r_t - \frac{S_{t+1} - S_t}{S_t} - r_t^{\mathrm{US}}\right)$.

## D. Transaction Costs

We also consider returns net of transaction costs by using bid and ask spreads. In particular, the net return from entering into a forward contract at time $t$ to go long the foreign currency in the forward market using the bid price ($F_t^b$) and selling the position at maturity in the spot market at time $t+1$ at the ask price ($S_{t+1}^a$) is calculated as: $\mathrm{RX}_{t+1}^L = \left(F_t^b - S_{t+1}^a\right)/S_t^a$. In the same vein, the short forward position in the foreign currency will offer a net excess return which is given by: $\mathrm{RX}_{t+1}^S = \left(F_t^a - S_{t+1}^b\right)/S_t^b$. We analyze results with and without bid–ask spreads as the inclusion of transaction costs boosts the measured volatility of excess returns and thus assigns a higher weight to less traded and illiquid currencies in our portfolio selection.

[10]Akram et al. (2008) show that CIP tends to hold for daily or lower frequencies.

## E. Revised Data

For our in-sample analysis, we consider revised data on unemployment, industrial production, 3-month Treasury Bills, and Consumer Price Index (CPI) from the Organization for Economic Cooperation and Development (OECD), the International Monetary Fund's International Financial Statistics (IFS), and Global Financial Data (GFD). Our monthly series span the period from Jan. 1990 to Mar. 2017. The in-sample analysis implies that the investors have access to revised macro-variables at the time of portfolio rebalancing. As a robustness test, we later relax this assumption by considering real-time measures of the variables of interest.[11]

## F. Vintage Data

We also collect real-time measures of harmonized unemployment and industrial production. This exercise is designed to make our analysis more realistic as it considers the information set available to policymakers at each point of time. Our out-of-sample analysis incorporates the editions of vintages of the OECD's *Original Release Data and Revisions Database* with 2 months lag. For example, for a February edition, we consider vintages of December. Similarly, for quarterly observations, for editions of the first quarter of the year, we collect vintages of the fourth quarter of the previous year.[12] This is a much stronger test of profitability as it would be expected to bias profitability downward due to the fact that investors tend to have access to broader information set at the time of rebalancing. The data span the period of Feb. 1999 until Mar. 2017. Our cross-section is also slightly smaller as vintages of unemployment rates and industrial production are not available for the Philippines and Thailand and vintages of unemployment rates are not available for Indonesia. Filtering out these countries and replacing Euro Zone countries with the single Euro Zone (i.e., the euro) reduces the universe of countries for this exercise to 15.

## G. Inflation Forecasts Data

We collect monthly survey data on forecasts of inflation from Consensus Economics. The data span the period from Jan. 1990 to Mar. 2017. The forecasts are reported in the first 2 weeks of the month.[13] To this end, our analysis is conservative and could affect our results downward as we treat them as end-of-month series even though this information was available to investors at the beginning of the month. However, the use of (slightly) stale forecasts enhances the robustness of our analysis. The forecasts provided by Consensus Economics reflect the average

[11]Data on industrial production for Indonesia is collected from the OECD database, May 2017 edition.

[12]We fill in missing values by down-filling; in other words, we keep the most recent value constant until a new value is realized.

[13]For a few countries (especially Latin American countries), Consensus Economics offers forecasts for the current and following year every 2 months at the beginning of the sample. For these cases, we consider the previous month forecast until a new forecast becomes available. Our results are similar for the raw data and they are available on demand.

monthly forecast obtained from different sources such as HSBC, UBS, JP Morgan Chase, Goldman Sachs, and Moody's.[14]

## H. Inflation Targeting

With respect to the institutional framework, many but not all currencies in our sample are issued by central banks that have an explicit inflation targeting mandate. However, even those without explicit inflation targets may be argued to have pursued de facto inflation targeting for much of the sample period. As noted earlier, while no central bank to date has published an explicit Taylor rule, a number of studies have fitted econometric equations relating short-term interest rates to measures of deviations of expected from target inflation and the output gap, demonstrating that the Taylor rule may provide a concise description of monetary policy behavior.[15] The statistical significance of the output gap in estimated Taylor rule equations (Bernanke et al. (1999), Clarida et al. (2000)) may represent either the fact that central banks are attempting to pursue macroeconomic stabilization rather than pure inflation targeting, or that the output gap is itself a predictor of inflation that is not captured in whatever series or method is being used to capture expected inflation.[16]

Supplementary Material Table A1 displays the inflation targets considered in our analysis for every country in our sample. For the central banks which offer a range of targets instead of a point target, we use the mean of the target range.

## I. Taylor Rule Signal

As discussed above, our forward-looking policy signal takes the following form: $\xi_t = \beta\left(\pi_t^f - \pi_t^*\right) + \gamma x_t - \lambda r_t$, for $x_t = y_t^{\text{gap}}$ or $x_t = -u_t^{\text{gap}}$ where $\beta$ is set equal to 1.5, $\gamma$ is set equal to 0.50 and $\lambda$ is estimated as the slope parameter from a cross-sectional regression of $\left[1.5\left(\pi_{it}^f - \pi_{it}^*\right) + 0.5x_{it}\right]$ onto $r_{it}$ at each time-series point $t$ in the sample, where the $i$-subscript indexes across countries (and is suppressed for

[14]For example, for Australia, the forecasts are gathered from BIS Shrapnel, Access Economics Suncorp, Westpac Banking Corp, JP Morgan Chase, Nomura Australia Macquarie Bank, Econ Intelligence Unit BT Funds, Management Centre of Policy Studies, HSBC Australia, Goldman Sachs JB Were, ANZ Group, Moody's Economy.com, National Australia Bank, UBS, and Commonwealth Bank Global Insight.

[15]A number of authors have, for example, estimated Taylor rules for the U.S. and Japan and have found that they are good descriptions of actual monetary policy, so there is an argument that they have in fact behaved in the past like inflation targeters using a Taylor rule (e.g., Clarida et al. (1998)). See also Bernanke (2015).

[16]In addition, to the question of whether inflation targeters condition interest rate decisions on the output gap, there is also the question of whether they condition on the exchange rate – in other words, whether the exchange rate should enter the Taylor rule. In a survey and discussion of the research on this issue, Taylor (2001) concludes that adding the current and/or lagged value of the exchange rate to a Taylor rule does not add value in macro model simulation exercises and has not generally been found to be significant in empirical work on Taylor rules, even for small open economies such as New Zealand (Huang, Margaritis, and Mayes (2001)). Taylor (2001) argues that this is because exchange rate changes are already factored into the inflation forecasts used in the standard forward-looking Taylor rule.

notational simplicity elsewhere, where the context is clear).[17] The residual from this regression, $\xi_{it}$ then becomes a signal of expected relative interest rate movements relative to the universe of countries in the analysis. Intuitively, a currency's short-term interest rates are expected to rise if forecast inflation is above target, conditional on weakness or strength in the economy (the output gap) and the current level of interest rates, and the cross-section regression then translates this into expected relative interest rate movements, which the signal predicts will affect future exchange rates because of future carry trades.

## J. Taylor Rule Portfolios

At the end of month $t$, we allocate currencies into portfolios based on their previous month policy signal. Thus, countries with high (low) levels of the Taylor rule signal, $\xi_{it}$, tend to exhibit higher (lower) expected inflation relative to the target after adjusting for the strength of the economy (via the output gap) and the current level of interest rates. To this end, we develop a zero-cost portfolio that goes long currencies of implied high rates while short selling currencies of countries with low implied interest rates, $\mathrm{HML}_{\mathrm{FTRu}}$ and $\mathrm{HML}_{\mathrm{FTRy}}$: $\mathrm{HML}_{\mathrm{FTRu}}$ corresponds to the forward-looking Taylor rule (FTR) signal that uses the unemployment gap ($u$) in its construction, while $\mathrm{HML}_{\mathrm{FTRy}}$ corresponds to the signal that uses detrended industrial production ($y$) in its construction, as discussed earlier.

We also analyze the performance of the forward-looking Taylor rule strategy with well-known currency portfolios. Specifically, we consider carry trade, momentum, value, and output gap-sorted currency portfolios.

## K. Momentum Portfolios

At the end of each month $t$, we allocate currencies into quintiles based on their previous month return and we rebalance the portfolios on a monthly basis, using a 1-month formation and formation period. The portfolios are sorted such that the first contains the worst performing currencies, or losers, and the fifth and last basket comprises the winner currencies. All portfolios are equally-weighted. The momentum strategy (i.e., WML) involves a long position in the best-performing currencies (i.e., Portfolio 5) while short-selling a basket of currencies with the poorest performance over the previous month (i.e., Portfolio 1).

## L. Carry Trade Portfolios

At the end of each month $t$, we allocate currencies into quintiles based on their forward discounts $(F_t - S_t)/S_t$ obtained at time $t-1$, assuming that covered interest rate parity (CIP) holds. Thus, the first basket of currencies consists of the lowest yielding or funding currencies and the last portfolio contains the highest yielding or investment currencies. All portfolios are equally-weighted. The carry trade strategy (CAR) involves a long position in high-yielding currencies (i.e., Portfolio 5) while short-selling low-yielding currencies (i.e., Portfolio 1).

[17]We obtain similar results for a $\gamma$ coefficient of $y_t^{\mathrm{gap}}$ set equal to 0.25 and the results are available on demand.

We also construct a market factor (DOL) which represents the average across portfolios each month.[18]

### M. Currency Value Portfolios

At the end of each month *t*, we allocate currencies into quintiles based on deviations from relative purchasing power parity. To this end, the first portfolio contains currencies with the lowest deviations from PPP over the previous 5 years and the last basket consists of a group of currencies with the highest deviations over the previous 5 years, following Asness, Moskowitz, and Pedersen (2013). The currency excess returns within each portfolio are equally weighted. The currency value strategy (VAL) involves a long position in undervalued currencies (i.e., Portfolio 5) and a short position in overvalued currencies (i.e., Portfolio 1).

### N. Output Gap Portfolios

At the end of each month *t*, we allocate currencies into quintiles based on a proxy for the output gap. This strategy exploits cross-sectional differences in the business cycle of the countries in our sample (e.g., Colacito et al. (2020)). To this end, the first portfolio contains currencies of weak economies and the last basket consists of a group of strong economies. The currency excess returns within each portfolio are equally weighted. The output gap strategy ($GAP_u$ or $GAP_y$) involves a long position in a basket of currencies of strong economies (i.e., Portfolio 5) and a short position in currencies of weak economies (i.e., Portfolio 1).

### O. Inflation Portfolios

At the end of each month *t*, we allocate currencies into quintiles based on vintages of realized inflation. This strategy exploits cross-sectional differences in inflation of the countries in our sample (e.g., Dahlquist and Hasseltoft (2020)). To this end, the first portfolio contains currencies of low-inflation economies and the last basket consists of a group of high-inflation economies. The currency excess returns within each portfolio are equally weighted. The inflation strategy (INF) involves a long position in a basket of currencies of high inflation economies (i.e., Portfolio 5) and a short position in currencies of low inflation economies (i.e., Portfolio 1).

## IV. Empirical Analysis

In this section, we provide summary statistics of our forward-looking Taylor rule strategy and associate its returns with existing currency investment strategies. Later, we examine the pricing ability of a zero-cost portfolio – that is constructed based on the Taylor rule signal – for the cross-section of carry trade, momentum, and value portfolios.

[18]See Lustig, Roussanov, and Verdelhan (2014). Specifically, we consider an equally weighted portfolio that goes long all foreign (non-U.S.) currencies when the average foreign short-term interest rate is greater than the home country's (USA) analogue as inferred through the average forward discount, defined as the mean of the forward discounts across portfolios each month.

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## A. Descriptive Statistics for the Taylor Rule Strategy

Table 1 reports summary statistics of currency portfolios sorted into quintiles based on the previous month implied interest rate and the corresponding spread portfolios. Specifically, we tabulate the annualized average currency excess returns, standard deviation, Sharpe ratios, skewness, and kurtosis as well as the first-order autocorrelations with the associated $p$-values. We report Newey and West (1987) heteroskedasticity and autocorrelation adjusted $t$-statistics with the optimal number of lags. Panel A shows results for currency portfolios that consider a forward-looking Taylor rule which incorporates the deviations of the unemployment rate from its natural level (e.g., $u_t^{\text{gap}}$) as a proxy for the output gap. We find that currency excess returns increase monotonically from low implied interest rate portfolios to high implied interest rate portfolios rendering a spread portfolio (e.g., $\text{HML}_{\text{FTRu}}$) with an annualized average excess return of 8.51% that is statistically significant. This finding indicates that investors who allocate their funds in countries with more pronounced inflation surprises tend to require a premium for financing such positions while countries with more stable inflation profiles provide a hedge in the bad state of the world when high implied interest rate currencies drop in value. Our results are robust to the presence of transaction costs as indicated by the positive (5.64%) and statistically significant payoff of net excess returns (e.g., $\text{HML}_{\text{TR}}^{\text{TC}}$).

TABLE 1

Descriptive Statistics of Taylor Rule Portfolios

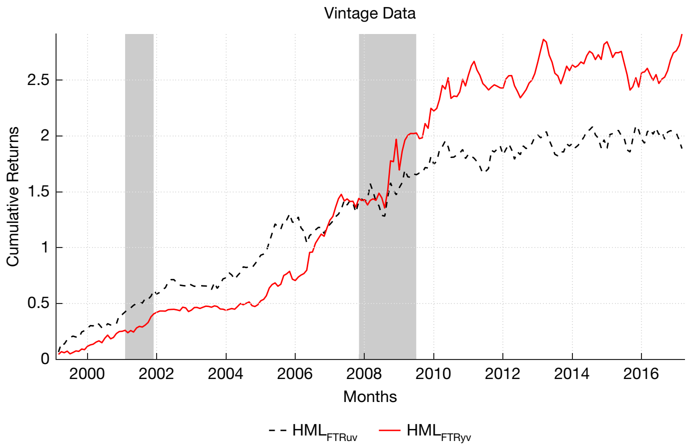
Table 1 reports descriptive statistics of payoffs to Taylor rule strategy. Panel A (Panel B) reports descriptive statistics for currency excess returns of portfolios sorted based on the Taylor rule signal that incorporates the unemployment rate (industrial production) as a proxy of output gap. In particular, $\text{HML}_{\text{FTR}}$ denotes the Taylor rule trade strategy that goes long (short) a basket of currencies with highest (lowest) Taylor rule signals (e.g., the surprise element of implied interest rates). The signal for $\text{HML}_{\text{FTRu}}$ considers the unemployment gap (e.g., $u_t^{\text{gap}}$) as proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5u_t^{\text{gap}} - \lambda r_t$, where $(\pi_t^f - \pi_t^*)$ denotes the difference between the inflation forecast and the corresponding target and $r_t$ represents the interest rate at time $t$. The signal for $\text{HML}_{\text{FTRy}}$ considers the detrended industrial production (e.g., Hodrick and Prescott (1980), (1997)) as a proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5y_t^{\text{gap}} - \lambda r_t$, at time $t$. We also report payoffs that are estimated in the presence of transaction costs (e.g., $\text{HML}_{\text{FTR}}^{\text{TC}}$) and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, and Sharpe ratio are annualized (the means are multiplied by 12 and the standard deviation by $\sqrt{12}$) and expressed in percentage points. *, **, and *** indicate the significance of the spread portfolios at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data span the period Jan. 1990–Mar. 2017.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $\text{HML}_{\text{FTRu}}$ | $\text{HML}_{\text{FTRu}}^{\text{TC}}$ |
|---|---|---|---|---|---|---|---|
| *Panel A. Taylor Rules with Unemployment* | | | | | | | |
| Mean | −1.11 | −0.61 | 1.98 | 1.99 | 7.40 | 8.51*** | 5.64** |
| Std. Dev. | 9.08 | 9.00 | 8.71 | 8.78 | 10.94 | 9.73 | 9.62 |
| SR | −0.12 | −0.07 | 0.23 | 0.23 | 0.68 | 0.88 | 0.59 |
| Skew | −0.94 | −0.66 | −0.62 | −0.40 | −0.43 | 0.31 | 0.20 |
| Kurt | 6.07 | 6.11 | 5.11 | 4.06 | 5.02 | 5.77 | 5.94 |
| AC(1) | 0.18 | 0.07 | 0.10 | 0.09 | 0.26 | 0.28 | 0.26 |
| *p*-Value | 0.00 | 0.19 | 0.07 | 0.09 | 0.00 | 0.00 | 0.00 |
| *Panel B. Taylor Rules with Industrial Production* | | | | | | | |
| Mean | −1.15 | −0.62 | 0.61 | 1.64 | 7.62 | 8.77*** | 5.86** |
| Std. Dev. | 9.02 | 9.16 | 9.46 | 8.86 | 10.84 | 9.78 | 9.69 |
| SR | −0.13 | −0.07 | 0.06 | 0.19 | 0.70 | 0.90 | 0.60 |
| Skew | −0.90 | −1.20 | −0.93 | −0.70 | −0.21 | 0.31 | 0.19 |
| Kurt | 5.67 | 7.82 | 7.45 | 5.38 | 4.24 | 5.38 | 5.43 |
| AC(1) | 0.20 | 0.08 | −0.07 | 0.06 | 0.29 | 0.23 | 0.21 |
| *p*-Value | 0.00 | 0.13 | 0.21 | 0.29 | 0.00 | 0.00 | 0.00 |

FIGURE 1

Cumulative Returns

Figure 1 displays cumulative returns of the forward-looking Taylor Rule Strategies. The graph displays results for real-time data for the period of Feb. 1999–Mar. 2017. The black dashed line represents a Taylor rule strategy that incorporates unemployment (e.g., $HML_{FTRuv}$) as a proxy for output gap and the red line shows a Taylor rule strategy that considers the detrended industrial production as a proxy for output gap (e.g., $HML_{FTRyv}$). The Taylor rule models consider fixed coefficients.




We also consider an alternative approach of calculating the Taylor rule signal using a different proxy for the output gap. Panel B of Table 1 shows results for currency portfolios that consider a forward-looking Taylor rule which incorporates a detrended measure of industrial production using the Hodrick and Prescott (HP) (1980), (1997) filter as a proxy for the output gap,[19] $HML_{FTRy}$.[20] Similarly to the previous results, we find that the portfolios of currencies sorted based on implied interest rates render positive and statistically significant payoffs even after controlling for transaction costs.

Figure 1 shows cumulative returns of the forward-looking Taylor rule strategies. The graph displays results for real-time data for the period of Feb. 1999–Mar. 2017. The black dashed line represents a Taylor rule strategy which incorporates unemployment as a proxy for output gap and the red line shows a Taylor rule strategy that considers the detrended industrial production as a proxy for output gap. The Taylor rule models in both cases are fixed-coefficient models. We find that the Taylor rule strategy based on the industrial production measure of the output gap performs slightly better. In addition, the strategy exhibits its best performance after 2000 and is flatter during the quantitative easing period with a rebound during the recent period (e.g., after the U.S. interest rate increase in Dec. 2015).

[19]Specifically, we consider the cyclical component (e.g., $c_{i,t}$) of the logarithm of industrial production (e.g., $y_{i,t}$) that is obtained after subtracting the trend provided by the filter (e.g., $c_{i,t} = y_{i,t} - y_{i,t}^{\text{trend}}$). Consistently with the literature, we consider a smoothing parameter ($\lambda$) of 14,400 for month data and 1,600 for quarterly data.

[20]As expected, the two signals exhibit very high correlations of about 0.98.

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### 1. Correlations with Other Currency Investment Strategies

It is natural to associate the cross-sectional predictive ability of a Taylor rule model with the carry trade strategy as the implicit interest rate of the Taylor rule model should be, in principle, highly correlated with its realized value. In our setting, however, we control for this aspect as we cross-sectionally orthogonalize our signal with respect to interest rate differentials in order to capture the surprise element of the domestic and foreign monetary policy. Nonetheless, we also investigated the connection between a forward-looking Taylor rule strategy and carry trade profitability.

Panel A of Table 2 shows correlations of the Taylor rule strategies with other currency investment strategies such as carry trade, currency momentum, currency value as well as output gap-sorted spread portfolios. We find that the forward-looking Taylor rules strategy is more corrected with the inflation component (e.g., $\mathrm{HML}_{\pi_t^f-\pi_t^*}$) rather than the output gap component (e.g., $\mathrm{HML}_{\mathrm{GAP}}$) of the strategy.

TABLE 2

Correlations with Other Investment Strategies and Uncertainty Factors

Table 2 reports correlations of payoffs to Taylor rule strategy and the corresponding signal with other investment strategies and uncertainty measures. Panel A reports correlations of the Taylor strategy with other currency investment strategies such as carry trades, currency momentum, currency value, and spread portfolios of currencies sorted based on output gap (e.g., $\mathrm{HML}_{\mathrm{GAP}}$) and inflation forecasts minus the target (e.g., $\mathrm{HML}_{\pi_t^f-\pi_t^*}$). Panel B reports correlations with U.S. equity momentum (e.g., $\mathrm{MOM}_{\mathrm{EQ}}$), U.S. equity value (e.g., $\mathrm{VAL}_{\mathrm{EQ}}$), credit risk premium of corporate (e.g., $\mathrm{CORP}_{\mathrm{XS}}$), and government bonds (e.g., $\mathrm{GOVT}_{\mathrm{XS}}$) and measures that capture the credit risk of the S&P500 index. We also consider the excess return of an equally-weighted commodity portfolio. Panel C offers correlations with uncertainty measures including includes the economic policy uncertainty of Baker et al. (2016), financial stress, migration and fear, monetary policy uncertainty, and geopolitical risk. $\mathrm{HML}_{\mathrm{FTR}}$ denotes the Taylor rule trade strategy that goes long (short) a basket of currencies with the highest (lowest) Taylor rule signals (e.g., the surprise element of implied interest rates). We also report *p*-values in parentheses. The data span the period Jan. 1990–Mar. 2017.

*Panel A. Currency Investment Strategies*

| | DOL | CAR | MOM | VAL | $\mathrm{HML}_{\mathrm{GAP}}$ | $\mathrm{HML}_{\pi_t^f-\pi_t^*}$ |
|---|---|---|---|---|---|---|
| $\mathrm{HML}_{\mathrm{FTRu}}$ | 0.13 | 0.18 | 0.09 | 0.14 | 0.05 | 0.42 |
| | (0.02) | (0.00) | (0.10) | (0.02) | (0.36) | (0.00) |
| $\mathrm{HML}_{\mathrm{FTRy}}$ | 0.11 | 0.18 | 0.11 | 0.20 | 0.10 | 0.49 |
| | (0.04) | (0.00) | (0.05) | (0.00) | (0.06) | (0.00) |

*Panel B. Equity Factors*

| | $\mathrm{MOM}_{\mathrm{EQ}}$ | $\mathrm{VAL}_{\mathrm{EQ}}$ | $\mathrm{CORP}_{\mathrm{XS}}$ | $\mathrm{GOVT}_{\mathrm{XS}}$ | $\mathrm{SP500}_{\mathrm{XS}}$ | COM |
|---|---|---|---|---|---|---|
| $\mathrm{HML}_{\mathrm{FTRu}}$ | −0.07 | 0.11 | −0.04 | 0.01 | −0.02 | −0.02 |
| | (0.19) | (0.05) | (0.52) | (0.91) | (0.73) | (0.76) |
| $\mathrm{HML}_{\mathrm{FTRy}}$ | −0.09 | 0.12 | −0.08 | 0.02 | −0.07 | −0.08 |
| | (0.10) | (0.03) | (0.16) | (0.75) | (0.21) | (0.14) |

*Panel C. Uncertainty Measures*

| | Economic Policy Uncertainty | Financial Stress | Migration Index | Fear Index | Monetary Policy Uncertainty | Geopolitical Risk |
|---|---|---|---|---|---|---|
| | Forward-looking Taylor rule portfolios | | | | | |
| $\mathrm{HML}_{\mathrm{FTRu}}$ | 0.08 | 0.11 | −0.08 | −0.02 | 0.07 | 0.02 |
| | (0.15) | (0.05) | (0.18) | (0.73) | (0.20) | (0.69) |
| $\mathrm{HML}_{\mathrm{FTRy}}$ | 0.00 | 0.11 | −0.08 | −0.08 | 0.02 | 0.02 |
| | (0.97) | (0.05) | (0.14) | (0.15) | (0.75) | (0.76) |
| | Forward-looking Taylor rule signals | | | | | |
| $\xi_{\mathrm{FTRu}}$ | −0.03 | −0.03 | 0.06 | −0.03 | −0.09 | 0.01 |
| | (0.62) | (0.56) | (0.25) | (0.58) | (0.10) | (0.90) |
| $\xi_{\mathrm{FTRy}}$ | −0.03 | −0.04 | 0.05 | −0.02 | −0.10 | 0.02 |
| | (0.63) | (0.52) | (0.35) | (0.66) | (0.08) | (0.75) |

We also consider the dollar factor (e.g., DOL) which serves as a proxy for overall foreign exchange market beta. In all cases, we find weak correlations of our investment strategy with these strategies. The highest correlations are related to the carry trade strategy but even here the maximum correlation coefficient is 0.18. This implies that the Taylor rule strategy is unrelated to the carry trade activity.

### 2. Correlations with Equity Investment Strategies

Panel B of Table 2 shows correlations of U.S. equity momentum (e.g., $\text{MOM}_{\text{EQ}}$), U.S. equity value (e.g., $\text{VAL}_{\text{EQ}}$), credit risk premium of corporate (e.g., $\text{CORP}_{\text{XS}}$), and government bonds (e.g., $\text{GOVT}_{\text{XS}}$) and measures that capture the credit risk of the S&P500 index (e.g., $\text{SP500}_{\text{XS}}$ (e.g., Asyanunt and Richardson (2017)).[21] We also consider the excess return of an equally-weighted commodity portfolio (e.g., Levine et al. (2018)).[22] We find that the Taylor rule strategy is negatively associated with equity momentum and the commodity factor in a statistically significant fashion but the correlations are very low in magnitude.

### 3. Correlations with Uncertainty Measures

Panel C of Table 2 displays correlations of the Taylor rule strategy as well as the cross-sectional average of the signal a number of measures of uncertainty.[23] Our universe of uncertainty measures includes economic policy uncertainty, financial stress, migration and fear, monetary policy uncertainty (e.g., Baker et al. (2016)) and geopolitical risk (e.g., Caldara and Iacoviello (2018)). The spread portfolios tend to show a weak negative and statistically significant relationship with the migration and fear measure but are unconnected with other uncertainty measures. On the other hand, the cross-sectional average of the signals exhibits a low and negative correlation with monetary policy uncertainty indicating that implied interest rates tend to increase as monetary policy uncertainty decreases.

## B. Out-of-Sample Performance

The previous analysis considers the information available to investors at the end of our sample. Here, we make a more realistic assumption by considering only the information that was available to investors at the time of the rebalancing of the portfolio. In particular, we employ vintages of harmonized unemployment and industrial production from Feb. 1999 and consider only information that was available to investors at each point at that time.[24] The data set spans the period of Feb. 1999 to Mar. 2017 and comprises a relatively smaller sample. In particular, we have a sample of 15 countries for unemployment and 16 countries

[21] $\text{CORP}_{\text{XS}}$ reflects the U.S. Long-Term Corporate Bond Total Return minus empirical-duration-matched long-term government bonds from U.S. Long-Term Government Bond Total Return. $\text{GOVT}_{\text{XS}}$ is defined as U.S. Long-Term Corporate Bond Total Return minus empirical-duration-matched long-term government bonds from U.S. Long-Term Government Bond Total Return. $\text{SP500}_{\text{XS}}$ is the S&P Composite Index Total Return minus U.S. Treasury Bill Total Return.

[22] The factors are collected from AQR's webpage (https://www.aqr.com/Insights/Datasets).

[23] We thank Nicholas Bloom for making these uncertainty measures available on his webpage (http://www.policyuncertainty.com/).

[24] This information usually refers to 2 months or a quarter lag from the edition date.

TABLE 3

Descriptive Statistics of Taylor Rule Portfolios: Out-of-Sample

Table 3 reports descriptive statistics of payoffs to Taylor rule strategy using vintage data. Panel A (Panel B) reports descriptive statistics for currency excess returns of portfolios sorted based on the Taylor rule signal that incorporates the unemployment rate (industrial production) as a proxy of output gap. In particular, $HML_{FTR}$ denotes the Taylor rule trade strategy that goes long (short) a basket of currencies with highest (lowest) Taylor rule signals (e.g., the surprise element of implied interest rates). The signal for $HML_{FTRuv}$ considers the unemployment gap (e.g., $u_t^{gap}$) as proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5u_t^{gap} - \lambda r_t$, where $(\pi_t^f - \pi_t^*)$ denotes the difference between the inflation forecast and the corresponding target and $r_t$ represents the interest rate at time $t$. The signal for $HML_{FTRyv}$ considers the detrended industrial production (e.g., Hodrick and Prescott (1980), (1997)) as a proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5y_t^{gap} - \lambda r_t$, at time $t$. We also report payoffs that are estimated in the presence of transaction costs (e.g., $HML_{FTR}^{TC}$) and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, and Sharpe ratio are annualized (the means are multiplied by 12 and the standard deviation by $\sqrt{12}$) and expressed in percentage points. *, **, and *** indicate the significance of the spread portfolios at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data span the period Feb. 1999–Mar. 2017.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $HML_{FTRuv}$ | $HML_{FTRuv}^{TC}$ |
|---|---|---|---|---|---|---|---|
| *Panel A. Unemployment* | | | | | | | |
| Mean | −1.95 | 1.23 | 0.84 | 1.61 | 4.21 | 6.16*** | 4.39** |
| Std. Dev. | 10.18 | 10.04 | 9.76 | 9.53 | 9.44 | 7.61 | 7.60 |
| SR | −0.19 | 0.12 | 0.09 | 0.17 | 0.45 | 0.81 | 0.58 |
| Skew | −0.98 | −0.75 | −0.57 | −1.05 | −0.28 | 0.39 | 0.37 |
| Kurt | 6.53 | 5.82 | 4.64 | 6.32 | 3.54 | 3.40 | 3.37 |
| AC(1) | 0.11 | 0.03 | 0.01 | 0.12 | 0.04 | 0.04 | 0.04 |
| *p*-Value | 0.10 | 0.62 | 0.91 | 0.09 | 0.57 | 0.51 | 0.56 |
| *Panel B. Industrial Production* | | | | | | | |
| Mean | −0.59 | 0.12 | −0.11 | 1.32 | 7.28 | 7.87*** | 5.78*** |
| Std. Dev. | 9.50 | 10.49 | 9.90 | 9.70 | 9.15 | 7.80 | 7.76 |
| SR | −0.06 | 0.01 | −0.01 | 0.14 | 0.80 | 1.01 | 0.74 |
| Skew | −0.63 | −1.19 | −0.87 | −0.44 | −0.57 | 0.34 | 0.32 |
| Kurt | 5.43 | 8.32 | 6.47 | 5.25 | 3.86 | 6.40 | 6.45 |
| AC(1) | 0.09 | 0.06 | 0.07 | 0.05 | 0.04 | −0.03 | −0.04 |
| *p*-Value | 0.17 | 0.38 | 0.33 | 0.45 | 0.54 | 0.69 | 0.57 |

for industrial production as Indonesia, Philippines, and Thailand are not available for unemployment and Philippines and Thailand are not available for industrial production. We view this as an additional robustness check of our results as the excluded countries are emerging economies with less tradable currencies. In addition, Germany and Spain are not included in the sample after the initiation of the Euro in Jan. 1999.

This exercise serves as an out-of-sample test as it considers real-time information for the investors. However, it will bias our results downward as it omits additional information that the investors could possess at the rebalancing date. Panel A of Table 3 shows portfolios of currency excess returns sorted based on real-time Taylor rule signals using vintages for unemployment in our Taylor rule specification. We find that the Taylor rule strategy offers a 6.16% annualized return with a Sharpe ratio of 0.81 which is statistically significant. The strategy is still significant after considering transaction costs rendering 4.39% per annum with a Sharpe ratio of 0.58. Unsurprisingly, these results render lower excess returns in comparison to the revised data but they remain highly economically and statistically significant. Panel B shows similar results when we proxy the output gap with detrended industrial production. In particular, we obtain an annualized return of 7.87% before transaction costs and 5.78% per annum after taking into consideration bid–ask spreads. Interestingly, the correlations of the Taylor rule portfolios with carry trade portfolio range from 9% to 20% indicating a lack of correlation between current carry trade activity and the forward-looking Taylor rule strategies.[25]

## C. Dynamic Forward-Looking Taylor Rule Strategies

Our analysis thus far has been based on Taylor rule signals constructed using fixed coefficients that are proposed in the literature without considering possible time-variation of the Taylor rule model. To relax this constraint, we also constructed Taylor rule signals based on constrained linear regression models with upper and lower bounds for the coefficients. The estimation is on the basis of a 36-month rolling window with at least 24 nonmissing observations. Specifically, we allow the coefficients on the output gap (whether measured by unemployment or industrial production) to vary between 0 and 4 and the slope coefficient on deviations of inflation expectation from the target to vary between 1 and 4.[26]

Panel A of Table 4 shows descriptive statistics of portfolios of currencies sorted based on the dynamic Taylor model with revised (e.g., $HML_{FTRu}$) as well as vintage data (e.g., $HML_{FTRuv}$). This specification includes the unemployment gap as a proxy for the output gap. Panel B offers the corresponding results for a dynamic Taylor rule model using detrended industrial production and reports results for both revised (e.g., $HML_{FTRy}$) and vintage data (e.g., $HML_{FTRyv}$). We find an improvement in the performance of the strategy for both data sets. In particular, both strategies offer higher currency excess returns and more pronounced Sharpe ratios. Supplementary Material Table A3 shows that our results are robust to the presence of bid–ask spreads.

Supplementary Material Figure A1 offers the average loadings of unemployment gap, detrended industrial production, and inflation. The left panel shows results for revised data and the right panel displays average coefficients for vintage data. We find a strong heterogeneity in the average loadings across countries. Specifically, for unemployment gap, we find that the coefficients are below one in absolute value. We observe a similar pattern when considering the detrended industrial production as a proxy for output gap with the difference that the loadings are larger in absolute value for a few countries. In addition, the average loadings of inflation are 1.5 for all the countries. We observe a similar pattern for vintage data.[27]

[25]Specifically, the correlations of forward-looking Taylor rule portfolios with carry trade portfolios are around 50% before orthogonalization and exhibit a maximum of 20% after orthogonalization indicating that they capture information over and above the one that it is embedded in nominal interest rates. Supplementary Material Figure A8 shows the constituents of our policy rule portfolios and the frequency of their appearance in the low and high implied interest rate portfolios. We offer a discussion in Supplementary Material Section A.3.1. The top graphs show results for the low-interest rate Taylor rule signals while the bottom graphs display results for high-interest signals. We find that the constituents of carry trade portfolios are very different to those appear in policy portfolios. Graph C of Supplementary Material Figure A8 shows the frequency of portfolios of currencies with low and high-interest rate differentials (e.g., carry trade portfolios). We find that the constituents of carry trade portfolios are very different to those appear in policy portfolios.

[26]The selection of these bounds is not crucial for our results.

[27]The estimated loadings of the forward-looking Taylor rule may deviate from the Central Banks's response to inflation and output changes as they capture not only the magnitude of the policy response but also the associated forecasting ability of the variables regarding the state of the economy.

TABLE 4

Dynamic Taylor Rule Models

Table 4 reports descriptive statistics of payoffs to Taylor rule strategy. Panel A reports descriptive statistics for currency excess returns of portfolios sorted based on the Taylor rule signal for the full sample and Panel B reports the corresponding summary statistics for the period Jan. 1990–Dec. 2007. In particular, $\mathrm{HML_{DFTR}}$ denotes the Taylor rule trade strategy that goes long (short) a basket of currencies with highest (lowest) Taylor rule signals (e.g., the surprise element of implied interest rates). The signal considers the unemployment gap (e.g., $u_t^{\mathrm{gap}}$) as proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.50u_t^{\mathrm{gap}} - \lambda r_t$, where $(\pi_t^f - \pi_t^*)$ denotes the difference between the inflation forecast and the corresponding target and $r_t$ represents the interest rate at time $t$. We also report payoffs are estimated in the presence of transaction costs (e.g., $\mathrm{HML_{DFTR}^{TC}}$) and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, and Sharpe ratio are annualized (the means are multiplied by 12 and the standard deviation by $\sqrt{12}$) and expressed in percentage points. *, **, and *** indicate the significance of the spread portfolios at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data span the period Jan. 1990–Mar. 2017 for revised data and the period Feb. 1999–Mar. 2017.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $\mathrm{HML_{DFTRu}}$ | $\mathrm{HML_{DFTRuv}}$ |
|---|---|---|---|---|---|---|---|
| *Panel A. Unemployment* | | | | | | | |
| Mean | −2.61 | 1.88 | 0.49 | 0.64 | 8.03 | 10.64*** | 5.85*** |
| Std. Dev. | 9.10 | 8.68 | 8.68 | 9.15 | 9.73 | 8.94 | 7.87 |
| SR | −0.29 | 0.22 | 0.06 | 0.07 | 0.83 | 1.19 | 0.74 |
| Skew | −1.14 | −0.68 | −0.29 | −0.29 | −0.19 | 0.33 | 0.46 |
| Kurt | 6.61 | 6.01 | 4.50 | 4.50 | 3.36 | 3.59 | 3.70 |
| AC(1) | 0.13 | 0.09 | −0.04 | 0.02 | 0.37 | 0.39 | 0.15 |
| *p*-Value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Panel B. Industrial Production* | | | | | | | |
| Mean | −1.84 | 1.74 | 0.24 | 1.04 | 7.61 | 9.45*** | 6.59*** |
| Std. Dev. | 8.93 | 8.73 | 8.75 | 8.88 | 9.77 | 8.76 | 8.23 |
| SR | −0.21 | 0.20 | 0.03 | 0.12 | 0.78 | 1.08 | 0.80 |
| Skew | −0.92 | −0.56 | −0.47 | −0.29 | −0.12 | 0.35 | 0.49 |
| Kurt | 5.62 | 5.44 | 4.40 | 4.57 | 3.36 | 3.30 | 3.95 |
| AC(1) | 0.14 | 0.05 | 0.00 | 0.04 | 0.39 | 0.40 | 0.04 |
| *p*-Value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

## D. Asset Pricing Tests

In this section, we investigate the ability of existing risk factors in the foreign exchange literature to explain the returns of the portfolios sorted based on forward-looking Taylor rule signals. Thus, our analysis examines whether a risk-based approach could explain the cross-sectional predictive ability of Taylor rule signals with currency premia.

### 1. Methods

Motivated by the macro-finance literature (e.g., Lustig et al. (2011), Menkhoff et al. (2012), and Filippou et al. (2018)), we examine the pricing ability of existing risk factors when considering as test assets the cross-section of currency returns sorted based on forward-looking Taylor rule signals. The currency excess return of each portfolio $j$ is denoted as $\mathrm{RX}^j$ where $j$ takes values from 1 to 6.[28] The risk-adjusted currency excess return, under the no-arbitrage conditions, should be zero and satisfy the Euler equation:

$$E_t\left[M_{t+1}\mathrm{RX}_{t+1}^j\right] = 0,$$

where $M_{t+1}$ represents a linear stochastic discount factor (SDF) in the risk factors $\phi_{t+1}$. Specifically, we focus our attention on the SDF of the form below:

[28]Here, we consider six instead of five portfolios so as to have a broader cross-section of currency returns. However, the results are robust when including five test assets.

$$M_{t+1} = \left[1 - b'\left(\phi_{t+1} - \mu_\phi\right)\right],$$

where $b$ is the vector of factor loadings and $\mu_\phi$ denotes the vector of expected values of the pricing factors (i.e., $\mu_\phi = E(\phi_{t+1})$). The beta representation of the model is calculated by the combination of above equations offering the following beta pricing model:

$$E\left[\mathrm{RX}^j\right] = \lambda'^{\beta^j},$$

where $\lambda = \Sigma_\phi b$ denotes the factor risk prices with $\Sigma_\phi = E[(\phi_t - \mu_\phi)(\phi_t - \mu_\phi)']$ representing the variance–covariance matrix of the risk factors and $b$ the factor loading. The regression coefficients $\beta^j$ are based on a contemporaneous regression of each currency excess return ($\mathrm{RX}^j_{t+1}$) on the risk factors ($\phi_t$).

We apply a Fama and MacBeth (FMB) (1973) 2-pass regression, where in the first stage we perform contemporaneous time-series regressions of currency portfolio excess returns on the risk factors. In the second stage, we run cross-sectional regressions of average portfolio returns on factor loadings, calculated in the previous step, so as to obtain the factor risk prices. Our specification allows for common mispricing in the currency returns as it includes a constant. We report both Newey and West (1987) $t$-statistics as well as Shanken (1992) $t$-statistics so as to guard against the potential error-in-variable issue that might arise due to the fact that the regressors are estimated in the second stage of the FMB regression.

## 2. Taylor Rule Portfolios

Table 5 displays asset pricing results for a 2-factor model that consists of the dollar factor (DOL) and forward-looking Taylor rule risk factor. Then we augment the model with one of either the carry (CAR), momentum (MOM), value (VAL), output gap (GAP), or inflation (INF) risk factors. We use as test assets six currency portfolios sorted based on lagged forward-looking Taylor rule signals. We consider portfolios that are sorted based on a Taylor rule signal which includes unemployment gap (left panel) or detrended output gap (right panel). We rebalance our portfolios on a monthly basis. Thus, we employ an SDF of the form below:

$$\begin{aligned} M_{t+1} = {} & 1 - b_{\mathrm{DOL}}(\mathrm{DOL}_{t+1} - \mu_{\mathrm{DOL}}) - b_{\mathrm{HML_{FTR}}}\left(\mathrm{HML}_{\mathrm{FTR}t+1} - \mu_{\mathrm{HML_{FTR}}}\right) \\ & - b_F(F_{t+1} - \mu_F), \end{aligned}$$

where DOL represents the dollar factor, $\mathrm{HML_{FTR}}$ is the forward-looking Taylor rule factor for unemployment (i.e., $\mathrm{HML_{FTRuv}}$) and output gap (i.e., $\mathrm{HML_{FTRyv}}$) and $F$ is a currency spread portfolio of the following set of factors $F$ = [CAR MOM VAL GAP INF]. Table 5 provides results for the second-pass of the FMB regression. We offer estimates for the implied risk factor prices ($\lambda$) and the corresponding Newey and West (1987) $t$-statistics (in square brackets) or $p$-values (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection and SH are the corresponding Shanken (1992) $t$-statistics. The cross-sectional performance of the models is also evaluated based on $\chi^2$, cross-sectional $R^2$, and HJ distance (following Hansen and Jagannathan (1997)). The $\chi^2$ test statistics test the null

TABLE 5

**Asset Pricing Tests: Taylor Rule Portfolios**

Table 5 reports asset pricing results for 2-factor and 3-factor models that comprise the DOL and forward-looking Taylor rule factors as well as carry, momentum, value, output gap, and inflation (denoted by $F$) risk factors. We use as test assets six currency portfolios sorted based on past forward-looking Taylor rule signals. Particularly, we consider the specification of the Taylor rule signal which includes unemployment gap (left panel) or detrended output gap (right panel). We rebalance our portfolios on a monthly basis. We report Fama and MacBeth (1973) estimates factor prices of risk ($\lambda$). We also display Newey and West (1987) $t$-statistics (in square brackets) or $p$-values (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection and SH are the corresponding values of Shanken (1992). The table also shows $\chi^2$, cross-sectional $R^2$, HJ distance following Hansen and Jagannathan (1997). We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream via Barclays and Reuters. *, **, and *** indicate the significance of the loadings at the 10%, 5%, and 1% levels based on Shanken (1992) standard errors. The data contain monthly series for the period Feb. 1999–Mar. 2017.

| | Factor Prices | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unemployment | | | | | | | Industrial Production | | | | | | |
| | $\lambda_{DOL}$ | $\lambda_{HML_{FTRuv}}$ | $\lambda_F$ | $\chi^2_{NW}$ | $\chi^2_{SH}$ | $R^2$ | HJ | $\lambda_{DOL}$ | $\lambda_{HML_{FTRyv}}$ | $\lambda_F$ | $\chi^2_{NW}$ | $\chi^2_{SH}$ | $R^2$ | HJ |
| | 0.06 | 0.01*** | | 8.16 | 7.70 | 0.90 | 0.06 | 0.09 | 0.01*** | | 9.52 | 8.68 | 0.96 | 0.11 |
| NW | [0.35] | [3.24] | | (0.15) | (0.17) | | (0.44) | [0.54] | [4.29] | | (0.09) | (0.12) | | (0.10) |
| SH | [0.35] | [3.22] | | | | | | [0.54] | [4.28] | | | | | |
| F = CAR | 0.06 | 0.01*** | −0.01 | 5.54 | 4.12 | 0.95 | 0.04 | 0.08 | 0.01*** | 0.02** | 2.27 | 1.61 | 0.96 | 0.03 |
| NW | [0.37] | [3.51] | [−1.66] | (0.35) | (0.53) | | (0.76) | [0.45] | [4.01] | [2.90] | (0.81) | (0.90) | | (0.91) |
| SH | [0.37] | [3.40] | [−1.44] | | | | | [0.45] | [3.96] | [2.48] | | | | |
| F = MOM | 0.06 | 0.01*** | 0.01 | 7.86 | 6.70 | 0.90 | 0.06 | 0.12 | 0.01*** | 0.03 | 6.63 | 3.04 | 0.99 | 0.04 |
| NW | [0.35] | [3.26] | [0.73] | (0.16) | (0.24) | | (0.34) | [0.69] | [3.85] | [1.70] | (0.25) | (0.69) | | (0.93) |
| SH | [0.35] | [3.17] | [0.67] | | | | | [0.68] | [3.64] | [1.15] | | | | |
| F = VAL | 0.06 | 0.01*** | 0.00 | 8.12 | 7.63 | 0.93 | 0.06 | 0.09 | 0.01*** | 0.00 | 9.48 | 8.60 | 0.98 | 0.10 |
| NW | [0.35] | [3.18] | [−0.17] | (0.15) | (0.18) | | (0.26) | [0.53] | [4.21] | [0.20] | (0.09) | (0.13) | | (0.17) |
| SH | [0.35] | [3.17] | [−0.17] | | | | | [0.53] | [4.18] | [0.19] | | | | |
| F = GAP | 0.00 | 0.00** | −0.01 | 7.72 | 6.76 | 0.93 | 0.06 | 0.00 | 0.01*** | −0.01 | 7.03 | 4.70 | 0.98 | 0.10 |
| NW | [0.35] | [2.62] | [−1.05] | (0.17) | (0.24) | | (0.29) | [0.46] | [4.22] | [−1.43] | (0.22) | (0.45) | | (0.12) |
| SH | [0.35] | [2.56] | [−0.99] | | | | | [0.46] | [4.15] | [−1.18] | | | | |
| F = INF | 0.00 | 0.01** | −0.02 | 6.99 | 5.00 | 0.92 | 0.05 | 0.00 | 0.01*** | 0.02 | 4.77 | 2.83 | 0.99 | 0.07 |
| NW | [0.40] | [2.61] | [−0.67] | (0.22) | (0.42) | | (0.80) | [0.40] | [3.80] | [1.95] | (0.44) | (0.73) | | (0.68) |
| SH | [0.40] | [2.42] | [−0.56] | | | | | [0.40] | [3.74] | [1.51] | | | | |

hypothesis that all pricing errors in the cross-section are mutually equal to zero. In addition, the cross-sectional pricing errors are estimated as the difference between the realized and predicted excess returns. The HJ distance is a model diagnostic that tests whether the distance of the SDF of the candidate model in squared forms and a group of acceptable SDFs is not different than zero.

Firstly, we examine the statistical significance of the factor risk prices of each factor (i.e., $\lambda_F$) as well as the forward-looking Taylor rule factor (i.e., $\mathrm{HML}_{\mathrm{HML}_{\mathrm{FTRuv}}}$ or $\mathrm{HML}_{\mathrm{HML}_{\mathrm{FTRyv}}}$) and the market factor (i.e., $\lambda_{\mathrm{DOL}}$). We start with the 2-factor model that includes a dollar factor and a Taylor rule risk factor. We find that the Taylor rule spread portfolios exhibit strong cross-sectional predictive power. This is perhaps not surprising as the Taylor rule factors serve as the slope factor of these test assets. We find that the Taylor rule prices of risk are always positive and significant based on both Newey and West (1987) and Shanken (1992) standard errors across Taylor rule-sorted portfolios. Moreover, the risk price of average excess return factor (DOL) is not statistically significant. This is due to the fact that all portfolios have a loading close to one with respect to this factor (e.g., level factor). For this reason, it cannot explain the cross-sectional variation in portfolio returns and it acts as a constant in the cross-sectional regression.[29] The cross-sectional $R^2$ takes the values

[29]The results are also verified by generalized method of moments (i.e., $\mathrm{GMM}_1$ and $\mathrm{GMM}_2$) estimates and they are available on demand. Specifically, in the first stage of the GMM ($\mathrm{GMM}_1$) we begin with an identity weighting matrix in order to examine whether the factors are able to price the cross-section of the currency excess returns in a similar manner. Then in the second stage ($\mathrm{GMM}_2$) we consider the weighting

of 90% for an unemployment-based Taylor rule and 96% for a Taylor rule that includes detrended industrial production. In all cases, we fail to reject the null hypothesis of zero pricing errors, regardless of the estimation procedure, at any standard significance level. Finally, we cannot reject the null hypothesis that the HJ distance is equal to zero for both specifications as they offer high $p$-values.

On the other hand, we find that spread portfolios that consider carry trade, momentum, value, output gap, and inflation strategies cannot explain the cross-section of Taylor rule portfolios as the factor risk prices are not statistically different from zero. One exception is the carry trade portfolio, which demonstrates strong pricing ability for Taylor rule portfolios with detrended output gap. However, this result is not robust to different subsample and other Taylor rule specifications. For example, we do not observe a similar performance for a Taylor rule model constructed using the unemployment gap and a slightly different set of currencies.[30] These findings highlight that forward-looking Taylor rule risk factors offer information over and above inflation and output gap factors (e.g., Dahlquist and Hasseltoft (2020)).[31]

Overall, we find that only an asset pricing model that includes the Taylor rule spread portfolios can price the cross-section of Taylor rule sorted portfolios based on statistical significance and goodness of fit.

## 3. Alternative Currency Portfolios

Here we consider the pricing ability of the Taylor rule factors when considering the cross-section of carry trade, momentum, value, output gap, inflation, and Taylor rule portfolios at the same time. Table 6 displays asset pricing tests for a 2-factor model that comprises the dollar factor (i.e., DOL) and the Taylor rules portfolio (e.g., $\text{HML}_{\text{FTRuv}}$ or $\text{HML}_{\text{FTRyv}}$). We consider 36 test assets (TA) that comprise six carry trade, momentum, value, output gap, inflation, and Taylor portfolios ($\text{TA} = [\text{PORT}_{\text{CAR}}, \text{PORT}_{\text{MOM}}, \text{PORT}_{\text{VAL}}, \text{PORT}_{\text{GAP}}, \text{PORT}_{\text{INF}}, \text{PORT}_{\text{FTR}}]$). We offer results for both Taylor rule specifications. We find that our 2-factor model is able to explain the cross-section of the aforementioned test assets as the price of risk of Taylor rule surprises is positive and highly significant rendering around 6% per annum. The adjusted $R^2$ range from 33% to 41% and we cannot reject the null that the pricing errors are jointly equal to zero, for the specification that includes the unemployment gap, as all $p$-values (reported in parentheses) are greater than 5%.

This finding is in accordance with the results of Lewellen et al. (2010), who show that it is relatively easy to construct risk factors that are able to price test assets with strong factor structure and limited cross-section. These authors recommend the consideration of a larger cross-section so as to alleviate these

matrix optimally by minimizing the difference between the objective functions under heteroskedasticity and autocorrelation consistent (HAC) estimates of the long-run covariance matrix of the moment conditions.

[30]Supplementary Material Table A4 shows the corresponding results for a combo strategy that sorts currencies into portfolios based on the sum of inflation and output gap (e.g., Dahlquist and Hasseltoft (2020)). We find that the forward-looking Taylor rule risk factor is highly significant and offers information over and above this factor.

[31]We would like to thank the referee for pointing this out.

TABLE 6

Asset Pricing Tests: Alternative Test Assets

Table 6 reports asset pricing results for a 2-factor model that comprises that DOL and the Taylor rule risk factors. We use as test assets 36 test assets (TA) that include carry trade, momentum, value, output gap, inflation portfolios, and Taylor rule portfolios. Particularly, we consider the specification of the Taylor rule signal which includes unemployment gap (Panel A) or detrended output gap (Panel B). We rebalance our portfolios on a monthly basis. We report Fama and MacBeth (1973) estimates of factor prices of risk ($\lambda$). We also display Newey and West (1987) $t$-statistics (in square brackets) or $p$-values (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection and SH are the corresponding values of Shanken (1992). The table also shows $\chi^2$, cross-sectional $R^2$, HJ distance following Hansen and Jagannathan (1997). We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream via Barclays and Reuters. *, **, and *** indicate the significance of the loadings at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data contain monthly series for the period Feb. 1999–Mar. 2017.

| | Factor Prices | | | | | |
|---|---|---|---|---|---|---|
| | $\lambda_{DOL}$ | $\lambda_{HML_{FTRv}}$ | $\chi^2_{NW}$ | $\chi^2_{SH}$ | $R^2$ | HJ |
| | Unemployment | | | | | |
| TA = [$PORT_{CAR}$, $PORT_{MOM}$, $PORT_{VAL}$, $PORT_{GAP}$, $PORT_{INF}$, $PORT_{FTRuv}$] | 0.09 | 0.01*** | 45.31 | 42.62 | 0.13 | 0.33 |
| NW | [0.48] | [3.03] | (0.11) | (0.18) | | (0.01) |
| SH | [0.48] | [3.01] | | | | |
| | Industrial Production | | | | | |
| TA = [$PORT_{CAR}$, $PORT_{MOM}$, $PORT_{VAL}$, $PORT_{GAP}$, $PORT_{INF}$, $PORT_{FTRyv}$] | 0.17 | 0.01*** | 9.52 | 8.68 | 0.96 | 0.11 |
| NW | [0.91] | [4.40] | (0.09) | (0.12) | | (0.10) |
| SH | [0.91] | [4.35] | | | | |

concerns.[32] Lewellen et al. (2010) also suggest that asset pricing models should be evaluated based on GLS $R^2$s. We find in Supplementary Material Table A5 that the GLS $R^2$ is one of the highest for the models that include the Taylor rule factor.[33] Another model with high GLS $R^2$ is a model that includes a dollar factor and a carry trade factor (e.g., Lustig et al. (2011)) but the differences with the Taylor rule model are not economically significant. Specifically, the Taylor rule model that proxies output gap based on industrial production is the best performing and the differences between the Taylor rule model that is based on unemployment and the carry trade model are not economically significant. In addition, the GRS statistic (Gibbons et al. (1989)) is the lowest among the competing models. Overall, we find that our model outperforms other foreign exchange asset pricing models as it renders the lowest GRS statistic.

## E. Forward-Looking and Backward-Looking Policy Rules

In this section, we investigate potential differences between signals based on forward-looking (i.e., FTR) and backward-looking (i.e., BTR) Taylor rule models for the cross-section of currency returns, by constructing currency portfolios that are sorted based on backward-looking Taylor rule signals constructed by replacing the inflation forecasts with lagged values of inflation for the previous year. Our backward-looking Taylor rule signals include vintages of inflation instead of

[32]In addition, they suggest that the pricing factors should be included as test assets in order to verify the ability of the risk factors to price themselves (i.e., $\lambda \approx E[R_F]$). We find that the results remain the same with or without the inclusion of the risk factors as test assets. The results are available on demand.

[33]Supplementary Material Table A5 shows the GRS statistic of Gibbons et al. (1989) where under the null hypothesis all alphas of the first pass regressions are jointly equal to 0. We find that even though we reject the null hypothesis for every model, the Taylor rule model offers one of the smallest GRS statistics.

inflation forecasts.[34] Supplementary Material Table A16 reports summary statistics of currency portfolios that are sorted based on lagged Taylor rules signals for both specifications. We find that the backward-looking Taylor rule strategy offers very high annualized returns for a spread portfolio that buys high implied interest rate portfolios and sells low implied interest rate portfolios (i.e., $\mathrm{HML}_{\mathrm{BTRuv}}$ or $\mathrm{HML}_{\mathrm{BTRyv}}$) that range from 3.59% to 5.92%.[35] However, this result is not robust across subsamples and Taylor rule specifications as the returns for the Taylor rule with unemployment gap is economically significant but not statistically significant. The signals are, however, orthogonal to interest rates and the portfolios exhibit low correlations with carry trades.

### 1. Relation Between BTR and FTR Portfolios

Panel A of Table 7 investigates the relationship between forward-looking and backward-looking Taylor rule portfolios. Specifically, we run a contemporaneous regression of the FTR spread portfolio on the BTR spread portfolio using vintage data for both Taylor rule specifications (i.e., using either unemployment or industrial production to estimate the output gap) as follows:

$$\mathrm{HML}_{\mathrm{FTR},t} = \alpha_{\mathrm{BTR}} + \beta_{\mathrm{BTR}} \mathrm{HML}_{\mathrm{BTR},t} + \varepsilon_t .$$

We find that, even though the two strategies are to some extend correlated, the BTR portfolios explain only 50%–60% of the variation of the FTR portfolios. However, the contemporaneous regression renders positive alphas ($\alpha_{\mathrm{BTR}}$) that are highly significant in both economic and statistical terms, offering around 2%–3% per annum. Thus, it is fair to conclude that the two strategies are not closely related and that accounting for the returns of BTR portfolios does not wipe out the excess returns to FTR portfolios.

### 2. Relation Between BTR, FTR, and Carry Trade Portfolios

Even though we constructed the Taylor rule signals to be orthogonal to current interest rate differentials, it is nevertheless worth dispelling any suspicion that the forward-looking Taylor rule signal profitability which we have documented is in some way due to carry trade activity. As we show in a previous section, the FTR portfolios exhibit very low correlations with carry trade portfolios indicating that the FTR signals offer information over and above interest rates. This is not surprising as the reduction in the correlations occurs after the orthogonalization of the Taylor rule signals with interest rates. Here, we will examine further this relationship for both BTR and FTR portfolios. Panel B of Table 7 shows the results of contemporaneous regressions of BTR and FTR spread portfolios on carry trade portfolios (i.e., CAR) of the form:

[34] A backward-looking Taylor rule model can be thought as a nested model or a special case of the forward-looking model if one considers the lagged inflation or its linear lagged combinations as a good predictor of future inflation. To this end, we should expect that the two measures are related but convey different marginal information.

[35] The strategy is statistically significant even after controlling for transactions costs based on bid–ask spreads, providing annualized excess returns of 1.84% to 3.77% with a highest Sharpe ratio of 49%.

TABLE 7

**Backward-Looking and Forward-Looking Taylor Rules**

Table 7 reports contemporaneous regressions of forward-looking on backward-looking Taylor rules as well as carry trade portfolios. Panel A reports contemporaneous regression of spread portfolios of forward-looking Taylor rules (e.g., $HML_{FTR}$) on backward-looking Taylor rule (e.g., $HML_{BTR}$) portfolios for both unemployment based and detrended industrial production forms of the Taylor rule model. Panel B show contemporaneous regressions of forward-looking Taylor rules or backward-looking Taylor rule spread portfolios on carry trade portfolios. Panels C–F show the corresponding results for inflation, output gap, momentum, and value portfolios. The alphas are annualized and expressed in percentage points. We report *t*-statistics in square brackets and adjusted *R*-squares ($\overline{R}^2$) The alphas are annualized. *, **, and *** indicate the significance of the spread portfolios at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data span the period Feb. 1999–Mar. 2017.

| | $HML_{FTRuv}$ | $HML_{FTRyv}$ | $HML_{BTRuv}$ | $HML_{BTRyv}$ |
|---|---|---|---|---|
| *Panel A. Taylor Rules* | | | | |
| $\alpha_{BTR}$ | 2.03** | 3.25*** | | |
| | [2.03] | [2.72] | | |
| $\beta_{BTR}$ | 0.81*** | 0.72*** | | |
| | [15.41] | [7.83] | | |
| $\overline{R}^2$ (in%) | 64.34 | 50.69 | | |
| *Panel B. Taylor Rules and Carry Trades* | | | | |
| $\alpha_{CAR}$ | 4.86** | 6.69** | 2.55 | 3.78 |
| | [2.44] | [2.00] | [1.45] | [1.34] |
| $\beta_{CAR}$ | 0.17 | 0.06 | 0.15 | 0.12 |
| | [1.47] | [0.50] | [1.47] | [1.19] |
| $\overline{R}^2$ (in%) | 3.97 | 0.27 | 3.22 | 2.46 |
| *Panel C. Taylor Rules and Output Gap Portfolios* | | | | |
| $\alpha_{GAP}$ | 6.48*** | 6.56*** | 3.87*** | 4.84*** |
| | [3.85] | [3.99] | [2.72] | [2.72] |
| $\beta_{GAP}$ | −0.33** | 0.47 | −0.46*** | 0.39 |
| | [−2.25] | [5.21] | [−4.87] | [6.48] |
| $\overline{R}^2$ (in%) | 8.45 | 21.39 | 17.04 | 14.57 |
| *Panel D. Taylor Rules and Inflation Portfolios* | | | | |
| $\alpha_{INF}$ | 4.92*** | 7.16*** | 3.27** | 4.87** |
| | [2.90] | [3.20] | [2.15] | [2.31] |
| $\beta_{INF}$ | 0.01 | 0.05 | 0.16* | 0.17* |
| | [0.13] | [0.53] | [1.84] | [1.75] |
| $\overline{R}^2$ (in%) | −0.47 | 0.03 | 4.51 | 4.39 |
| *Panel E. Taylor Rules and Momentum* | | | | |
| $\alpha_{MOM}$ | 6.10*** | 7.00*** | 3.57** | 5.18*** |
| | [3.60] | [4.00] | [2.44] | [2.63] |
| $\beta_{MOM}$ | 0.10 | 0.08 | 0.04 | 0.08 |
| | [1.15] | [1.05] | [0.54] | [0.93] |
| $\overline{R}^2$ (in%) | 0.65 | 0.56 | −0.28 | 0.39 |
| *Panel F. Taylor Rules and Value* | | | | |
| $\alpha_{VAL}$ | 5.71*** | 8.03*** | 3.32** | 6.04*** |
| | [3.22] | [4.27] | [2.18] | [3.00] |
| $\beta_{VAL}$ | 0.15* | 0.07 | 0.07 | 0.03 |
| | [1.86] | [1.16] | [0.84] | [0.48] |
| $\overline{R}^2$ (in%) | 2.93 | 0.52 | 0.39 | −0.31 |

$$\mathrm{HML}_{\mathrm{TR},t} = \alpha_{\mathrm{CAR}} + \beta_{\mathrm{CAR}}\mathrm{CAR}_t + \epsilon_t, \text{ where } \mathrm{TR} = \mathrm{FTR},\mathrm{BTR}.$$

Interestingly, we find that BTR portfolios exhibit very high correlations with carry trade portfolios. In particular, the carry trade portfolios explain as high as 3% of the profitability of BTR portfolios with an intercept that is statistically insignificant. Thus, we can conclude that BTR portfolios do not offer any economic value over and above carry trade portfolios. On the other hand, we show that carry trade portfolios can explain as low as 3.97% of the variation of the FTR spread portfolios. In addition, the intercept (e.g., $\alpha_{\text{CAR}}$) of the regression is statistically and economically significant. This finding implies that the carry trade does not explain the economically and statistically significant strong performance of the forward-looking Taylor rule signal.

### 3. Relation Between BTR, FTR, and Other Currency Investment Strategies

We also show results for other investment strategies such as inflation, output gap, momentum, and value.[36] We examine further this relationship for both BTR and FTR portfolios. Panel C of Table 7 shows results of contemporaneous regressions of BTR and FTR spread portfolios on output gap portfolios (i.e., GAP) and find that they explain a low percentage of the variation of the FTR spread portfolios and the same holds for BTR portfolios rendering significant alphas that are as high as 7% for FTR and 4.9% for BTR portfolios.[37] Similarly, Panel D of Table 7 shows results for inflation portfolios (i.e., INF) and finds that they cannot explain the variation of FTR portfolios rendering alphas of about 7%. This highlights the low correlations between current inflation and inflation forecasts. In addition, our previous analysis shows that sorting based on inflation or output gap (e.g., Dahlquist and Hasseltoft (2020)) exhibits different dynamics from sorting based on Taylor rule specifications. On the other hand, the inflation portfolios explain 4.5% of the variation of BTR portfolios offering alphas of 4.9%.[38] Panel D (Panel E) offers results for momentum and value portfolios and we find that both strategies cannot explain the variation of Taylor rule portfolios offer very high and statistically significant alphas for both strategies.[39]

## F. Risk or Mispricing?

The profitability of forward-looking Taylor rule strategies could stem from risk, mispricing, or data snooping. In the next section, we show that our results are not due to data mining or data snooping. Thus, in this section, we turn our attention to risk or mispricing explanations.[40] In previous sections, we showed that the forward-looking Taylor rule factor loadings exhibit strong predictability for currency returns. This is consistent with investors requiring a risk premium for holding currencies with high implied interest rates, while currencies with low implied interest rates offer lower returns as they provide a hedge in the bad state of the world when high implied interest rate currencies drop in value.

[36] We would like to thank the referee for suggesting that we investigate these further investment strategies.

[37] In our regressions, we use the output gap that is based on industrial production (unemployment) for Taylor rule specifications that include the corresponding variables.

[38] Supplementary Material Figure A2 shows that the correlations of the ranks of inflation, output gap, and combo portfolios with the rank of forward-looking Taylor rule portfolios are very low indicating the disconnection of forward-looking Taylor rules with these strategies.

[39] Supplementary Material Table A6 shows the corresponding results and combo portfolios. We find that the forward-looking Taylor rule strategy offers very high alphas that are statistically significant.

[40] This section was added following the helpful suggestions of an anonymous referee.

### Analysts' Errors

We examine the predictive ability of Taylor rules for errors of analysts' forecasts. Our conjecture is that analysts' forecasts determine the expectations of the investors and deviations from the realized values could create mispricing. Thus, we expect that analysts' errors could partly drive currency mispricing. If the returns to the Taylor rule portfolios could be attributed to mispricing, the Taylor rule factor could contain important information for future analysts' errors.[41] To this end, we estimate a predictive panel regression model with country-fixed effects of analysts' errors on the Taylor rule factor. Specifically, the model takes the following form:

$$\widehat{\Delta S}_{i,t+1} - \Delta \mathrm{S}_{i,t+1} = \alpha_i + \beta \mathrm{TR}_{i,t} + \epsilon_{i,t+1}, \text{ where TR} = \text{FTRu,FTRy},$$

where $\widehat{\Delta S}_{i,t+1} - \Delta \mathrm{S}_{i,t+1}$ represent the analysts' forecasts that are defined as the difference between the forecast of the exchange rate change minus the realized exchanged rate change of currency $i$ at time $t+1$. $\mathrm{TR}_{i,t}$ is the Taylor rule measure per currency of currency pair $i$ at time $t$ (e.g., the month before the reporting of the forecast) and $\alpha_i$ denotes country fixed-effects. The standard errors are clustered by country. Table 8 shows that the Taylor rule factors cannot explain analysts' errors. These results are robust to different specifications of the measure.[42] Overall, therefore, we find that the strategy is not related to currency mispricing.[43]

TABLE 8

Taylor Rule Portfolios and Mispricing

Table 8 reports coefficients of contemporaneous regressions of spread Taylor rule portfolios using revised data. We show results for Taylor rules spread portfolios that are based on revised data on unemployment ($\mathrm{HML_{FTRu}}$) and industrial production ($\mathrm{HML_{FTRy}}$). We display Newey and West (1987) $t$-statistics (in square brackets). The excess returns are expressed in percentage points. The constant is annualized. We show results for predictive panel regressions with country-fixed effects of analysts' errors on the Taylor rule measures the month before the forecast. The standard errors are clustered by country. We define analysts' errors as the difference between the spot exchange rate change forecast and the realized exchange rate change (the exchange rate changes have a negative sign). The data are collected from Datastream via Barclays and Reuters. *, **, and *** indicate the significance of the loadings at the 10%, 5%, and 1% levels. The data contain monthly series for the period Feb. 1990–Mar. 2017.

| | Analysts' Forecasts | |
|---|---|---|
| | $\widehat{\Delta S} - \Delta S$ | $\widehat{\Delta S} - \Delta S$ |
| $\alpha$ | 0.30***<br>[5.39] | 0.30***<br>[4.76] |
| $\beta_{\mathrm{FTRu}}$ | −2.49<br>[−0.90] | |
| $\beta_{\mathrm{FTRy}}$ | | −3.12<br>[−1.00] |
| FE | Yes | Yes |
| $\bar{R}^2$ (in%) | 1.15 | 1.28 |

[41]There is mixed evidence regarding the role of analysts in stock mispricing (e.g., Grinblatt, Jostova, and Philipov (2016), Engelberg, McLean, and Pontiff (2020)).

[42]Supplementary Material Table A13 shows that our results are robust to an alternative definition of analysts' forecasts that is defined based on differences between the spot exchange rate forecast and the realized spot exchange rate. We find in Supplementary Material Table A14 similar results for vintage data.

[43]We also examine whether the profitability of the strategies declines after the publication of the seminal Henderson and McKibbin (1993) and Taylor (1993) papers in Dec. 1993, and find no such effect. We show results in Supplementary Material Table A15 and Supplementary Material Figures A3–A7 and we discuss the results in Supplementary Material Section A.3.2.

# V. Robustness and Other Specification Tests

In this section, we perform different robustness checks so as to examine further the performance of the Taylor rule strategies. Specifically, we consider differ methods of detrending output gap, different subperiods, alternative asset pricing models, and other specification tests.

## A. Data Snooping Tests

One concern regarding our trading strategy could be that the reported returns are subject to data snooping (i.e., the documented returns are an artefact of chance error) and so they are spurious. In other words, the performance of the Taylor rule strategy could be sample-specific and might behave differently in periods that predate or follow our sample-period. Our study considers both revised and vintage data so as to ensure data availability at the time of rebalancing but it ignores potential changes in the performance of the strategy for larger samples. To this end, we perform White's (2000) reality check using a stationary bootstrap of Politis and Romano (1994) so as to guard against this issue.[44] We find in Supplementary Material Table A7 and Supplementary Material Section A.3.3 that the Taylor rule which includes detrended industrial production is the best-performing strategy. In addition, we show that none of the White $p$-values exceed the significance level of 5%, indicating that there is evidence of profitability even after controlling for data snooping as the null hypothesis of no outperformance is always rejected for all performance measures at standard significance levels. The results are also robust to the consideration of transaction costs.

## B. Alternative Measures of Output Gap

The previous sections define the cyclical component of output as the difference between the logarithm of industrial production and its trend. The trend component is not observed and it is estimated based on the HP filter. Here, we consider different methods of estimating the trend component (i.e., $\tau_{i,t}$) of output. Similar to Colacito et al. (2020), we examine the robustness of our model when the trend component is estimated based on the Baxter-King filter, and the linear projection of Hamilton (2018). We also include a quadratic time trend (e.g., Orphanides and Norden (2002)).[45]

Table 9 offers summary statistics of currency portfolios sorted based on a forward-looking Taylor rule signal that considers detrended output following the methods that we analyze above.[46] Specifically, Panel A (Panel B) shows descriptive statistics of currency portfolios sorted on Taylor rule signals that are sorted based on a Taylor rule signal with a detrended output gap estimated based on the Baxter-King Filter (linear projection). Panel C shows results for the Taylor rule sorted portfolios that incorporate a quadratic time trend. In any case, we find that the Taylor rule

[44]Our bootstrap procedure follows Politis and Romano (1994) and is described in detail in Supplementary Material Section A1.

[45]We offer detailed descriptions of these alternative output gap measures in Supplementary Material Section A.3.4.

[46]The results for unemployment are similar and are available upon request.

TABLE 9

**Robustness: Different Measures of Output Gap**

Table 9 reports descriptive statistics of payoffs to Taylor rule strategy using vintage data. Panel A (Panel B) reports descriptive statistics for currency excess returns of portfolios sorted based on the Taylor rule signal that incorporates the unemployment rate (industrial production) as a proxy of output gap. In particular, $\text{HML}_{\text{FTR}}$ denotes the Taylor rule trade strategy that goes long (short) a basket of currencies with highest (lowest) Taylor rule signals (e.g., the surprise element of implied interest rates). The signal for $\text{HML}_{\text{FTRu}}$ considers the unemployment gap (e.g., $u_t^{\text{gap}}$) as proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5u_t^{\text{gap}} - \lambda r_t$, where $(\pi_t^f - \pi_t^*)$ denotes the difference between the inflation forecast and the corresponding target and $r_t$ represents the interest rate at time $t$. The signal for $\text{HML}_{\text{FTRy}}$ considers the detrended industrial production (e.g., Hodrick and Prescott (1980), (1997)) as a proxy of output gap and takes the following form: $\xi_t = 1.5(\pi_t^f - \pi_t^*) - 0.5y_t^{\text{gap}} - \lambda r_t$, at time $t$. We also report payoffs that are estimated in the presence of transaction costs (e.g., $\text{HML}_{\text{FTR}}^{\text{TC}}$) and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, and Sharpe ratio are annualized (the means are multiplied by 12 and the standard deviation by $\sqrt{12}$) and expressed in percentage points. *, **, and *** indicate the significance of the spread portfolios at the 10%, 5%, and 1% levels that are estimated using Newey and West (1987) standard errors with the optimal number of lags. The data span the period Feb. 1999–Mar. 2017.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $\text{HML}_{\text{FTRyv}}$ | $\text{HML}_{\text{FTRyv}}^{\text{TC}}$ |
|---|---|---|---|---|---|---|---|
| *Panel A. Baxter-King Filter* | | | | | | | |
| Mean | −1.59 | 0.42 | 2.49 | 2.45 | 6.35 | 7.94*** | 7.93*** |
| Std. Dev. | 10.11 | 10.86 | 9.53 | 9.58 | 9.95 | 8.42 | 8.38 |
| SR | −0.16 | 0.04 | 0.26 | 0.26 | 0.64 | 0.94 | 0.95 |
| Skew | −0.76 | −1.08 | −0.61 | −0.47 | −0.67 | 0.19 | 0.19 |
| Kurt | 4.74 | 6.80 | 5.01 | 4.08 | 4.18 | 3.51 | 3.55 |
| AC(1) | 0.12 | 0.07 | 0.09 | 0.07 | 0.04 | 0.04 | 0.03 |
| *p*-Value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Panel B. Linear Projection* | | | | | | | |
| Mean | 0.50 | 2.28 | 2.59 | −0.67 | 5.65 | 5.15*** | 3.35** |
| Std. Dev. | 9.89 | 10.43 | 9.96 | 9.97 | 9.92 | 7.77 | 7.75 |
| SR | 0.05 | 0.22 | 0.26 | −0.07 | 0.57 | 0.66 | 0.43 |
| Skew | −0.69 | −0.70 | −0.79 | −0.92 | −0.86 | 0.41 | 0.37 |
| Kurt | 6.48 | 4.91 | 5.31 | 6.68 | 5.66 | 6.75 | 6.69 |
| AC(1) | 0.08 | 0.13 | −0.01 | 0.08 | 0.01 | −0.17 | −0.20 |
| *p*-Value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Panel C. Quadratic Time Trend* | | | | | | | |
| Mean | 0.22 | 0.43 | 0.59 | −0.25 | 6.90 | 6.68*** | 4.60** |
| Std. Dev. | 9.83 | 9.92 | 10.19 | 9.66 | 8.93 | 8.09 | 8.04 |
| SR | 0.02 | 0.04 | 0.06 | −0.03 | 0.77 | 0.83 | 0.57 |
| Skew | −0.80 | −0.86 | −0.73 | −0.47 | −0.72 | 0.62 | 0.61 |
| Kurt | 6.01 | 5.96 | 5.85 | 5.12 | 4.80 | 6.41 | 6.55 |
| AC(1) | 0.07 | 0.05 | 0.02 | 0.13 | 0.02 | −0.09 | −0.10 |
| *p*-Value | 0.31 | 0.46 | 0.78 | 0.07 | 0.81 | 0.18 | 0.14 |

strategy offers positive and statistically significant average excess returns even after controlling for the implementation cost of the strategies. Thus, the method employed in order to estimate the trend component of output does not affect our results.

## C. Different Asset Pricing Models

Here we consider alternative asset pricing models that could capture the cross-section of forward-looking Taylor rule portfolios. Specifically, we examine whether global volatility (VOL), global illiquidity (ILLIQ) of Menkhoff et al. (2012), global risk aversion (CORR) of Mueller, Stathopoulos, and Vedolin (2017), and global political risk (GPR) of Filippou et al. (2018) are priced in the cross-section of Taylor rule portfolios.[47] We consider factor mimicking portfolios

[47]Supplementary Material Section A.2 offers a detailed description of the variables.

of the aforementioned variables as they are not tradable factors. In particular, we project the factors on the six portfolios and obtain their fitted values. Thus, we employ an SDF of the following form: $M_{t+1} = 1 - b_{\mathrm{FM}}(\mathrm{FM}_{t+1} - \mu_{\mathrm{FM}}) - b_{\mathrm{HML}_{\mathrm{FTR}}}\left(\mathrm{HML}_{\mathrm{FTR}_{t+1}} - \mu_{\mathrm{HML}_{\mathrm{FTR}}}\right)$, where FM represents a currency spread portfolio of the following set of mimicking portfolios FM = [FVOL FILLIQ FCORR FGPR]. We omit the DOL factor as it explains none of the cross-sectional variations in currency returns sorted based on Taylor rule signals. Thus, our 2-factor model is a parsimonious model that replaces the dollar factor with the Taylor rule high-minus-low portfolio and includes one of the FM factors.

Overall, we find in Supplementary Material Table A8 that the abnormal returns offered by currency portfolios sorted based on forward-looking Taylor rule models cannot be explained by other risk factors in the literature with the exception of the global political risk measure which exhibits weak predictive power. Only the Taylor rule spread portfolios can capture a significant part of the cross-sectional variation of the test assets of interests as they serve as slope factors.

## D. Implications for Other Currency Investment Strategies

We examine the cross-sectional predictive ability of our forward-looking Taylor rule factor for other currency investment strategies, namely carry trades, momentum, and value. Thus, we consider as test assets six currency portfolios for each of the aforementioned strategies. Table 10 shows results for our 2-factor asset pricing model that comprises the DOL factors and forward-looking Taylor rule portfolios that goes long currencies with high implied rates while short-selling currencies with low implied rates using vintage data. We find that our 2-factor asset pricing model can explain the cross-section of carry trade portfolios. We also find that the model demonstrates strong predictive power for currency

TABLE 10

Robustness: Asset Pricing Tests: Other Currency Investment Strategies

Table 10 reports asset pricing results for a 2-factor model that comprises the DOL and carry, momentum, value, or Taylor rule (denoted by F) risk factors. We use as test assets six currency carry trade (i.e., $\mathrm{PORT}_{\mathrm{CAR}}$), momentum (i.e., $\mathrm{PORT}_{\mathrm{MOM}}$) or value (i.e., $\mathrm{PORT}_{\mathrm{VAL}}$) portfolios. Particularly, we consider the specification of the Taylor rule signal which includes unemployment gap (Panel A) or detrended output gap (Panel B). We rebalance our portfolios on a monthly basis. We report Fama and MacBeth (1973) estimates of factor prices of risk ($\lambda$). We also display Newey and West (1987) $t$-statistics (in square brackets) or $p$-values (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection and SH are the corresponding values of Shanken (1992). The table also shows $\chi^2$, cross-sectional $R^2$, HJ distance following Hansen and Jagannathan (1997). We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream via Barclays and Reuters. *, **, and *** indicate the significance of the loadings at the 10%, 5%, and 1% levels based on Shanken (1992) standard errors. The data contain monthly series for the period Feb. 1999–Mar. 2017.

| | Factor Prices | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unemployment | | | | | | Industrial Production | | | | | |
| | $\lambda_{\mathrm{DOL}}$ | $\lambda_{\mathrm{HML}_{\mathrm{FTRuv}}}$ | $\chi^2_{\mathrm{NW}}$ | $\chi^2_{\mathrm{SH}}$ | $R^2$ | HJ | $\lambda_F$ | $\lambda_{\mathrm{HML}_{\mathrm{FTRyv}}}$ | $\chi^2_{\mathrm{NW}}$ | $\chi^2_{\mathrm{SH}}$ | $R^2$ | HJ |
| TA = $\mathrm{PORT}_{\mathrm{CAR}}$ | 0.12 | 0.04*** | 28.14 | 7.46 | 0.80 | 0.17 | 0.10 | 0.04*** | 37.24 | 7.58 | 0.59 | 0.17 |
| NW | [0.67] | [7.17] | (0.00) | (0.19) | | (0.00) | [0.58] | [6.38] | (0.00) | (0.18) | | (0.00) |
| SH | [0.64] | [3.82] | | | | | [0.55] | [2.93] | | | | |
| TA = $\mathrm{PORT}_{\mathrm{MOM}}$ | 0.14 | 0.03*** | 3.06 | 0.88 | 0.95 | 0.07 | 0.15 | 0.03*** | 11.87 | 4.05 | 0.66 | 0.07 |
| NW | [0.81] | [5.04] | (0.69) | (0.97) | | (0.34) | [0.85] | [4.94] | (0.04) | (0.54) | | (0.38) |
| SH | [0.78] | [2.75] | | | | | [0.83] | [2.95] | | | | |
| TA = $\mathrm{PORT}_{\mathrm{VAL}}$ | 0.21 | 0.00 | 21.31 | 21.14 | 0.06 | 0.11 | 0.19 | 0.02 | 18.33 | 10.97 | 0.06 | 0.09 |
| NW | [1.17] | [0.08] | (0.00) | (0.00) | | (0.18) | [1.08] | [1.22] | (0.00) | (0.05) | | (0.62) |
| SH | [1.17] | [0.08] | | | | | [1.07] | [0.95] | | | | |

momentum indicating the role of monetary policy in return continuation of currency portfolios.[48]

## E. Alternative Sample Periods

Supplementary Material Table A2 examines the profitability of the Taylor rule factors for different subperiods. Specifically, we investigate the effect of the recent financial crisis and the implementation of Quantitative Easing (QE) that was adopted by major Central Banks in the profitability of the factor. To this end, we consider the subperiod of Jan. 1999 to Dec. 2007 and the sub-period of Jan. 2008 until the end of the sample. Panel A shows results for a Taylor rule that considers the unemployment gap and Panel B reports results for a Taylor rule specification with detrended industrial production. We find the latter case that Taylor rule portfolios are highly significant for both periods for both dynamic and nondynamic rules. For the Taylor rule which includes the unemployment gap, we find that in a few cases the payoffs are economically significant but statistically significant. Interestingly, the profitability of strategies before 2007 is mainly driven by the long leg of the trade while the returns of the strategy post-2007 are characterized by the variation of the short leg of the trade as the low implied interest rate currencies tend to depreciate more against the U.S. dollar.[49]

## F. Tradability

Here we apply different filters in the data so as to ensure that the currencies in our portfolios are tradable at the time of rebalancing. To this end, we apply different filters that include in our analysis only currency-time combinations that satisfy specific conditions. In particular, we consider country-time pairs that have a non-negative value on the Chinn and Ito (2006) capital account openness index, and their currencies belong in the exchange rate regime 3 or 4 of the IMF coarse classification.[50] Supplementary Material Table A9 displays summary statistics of portfolios of currencies sorted based on Forward-looking Taylor rule models for both specification of output gap using vintage data. The set of currencies that we consider in this exercise satisfy the aforementioned filters. We find that our results are improved for both Taylor rule specifications and they are robust even after controlling for transaction costs.

## G. Inflation Forecasts for the Following Year

Our previous analysis considers inflation forecasts for the current year. Here we assess the cross-sectional predictive ability of the signals when including

[48] We also find weak evidence of cross-sectional predictability for portfolios of currencies that are sorted based on yield curve slopes (e.g., Lustig, Stathopoulos, and Verdelhan (2019)). Consistently with Lustig et al. (2019), we find that inflation and inflation expectations offer limited information for yield currency portfolios. We show results in Supplementary Material Table A11. We thank the referee for encouraging us to address this issue.

[49] Schularick and Taylor (2012) show that Taylor rule models perform poorly during crisis periods as credit measures such as leverage and nonmonetary liabilities become more important.

[50] This filter deletes currencies that are inside a pre-announced crawling band of ±2%, outside a de facto crawling band of ±5%, outside a moving band of ±2%, or those that are not in a free float.

inflation forecasts of the following year. We should expect a similar result as the central bank forecast horizon is generally 2 years. Supplementary Material Table A12 shows summary statistics of Forward-looking Taylor rule portfolios that include inflation forecasts of the following year. We find very strong cross-sectional predictive ability as the spread portfolios offer to annualize returns that range from 3.18% to 6.71% with Sharpe ratios that range from 54% to 75%. The results are robust for a specification that includes detrended industrial production or unemployment gap.

### H. Foreign Investors

Our previous analysis takes the U.S. investor's viewpoint when constructing the Taylor rule signals. We also investigate the performance of the forward-looking Taylor rule portfolios when considering different base currencies. Supplementary Material Table A10 shows descriptive statistics from the perspective of a foreign investor. We find that our results are very similar -or improved in a few cases- regardless of the base currency. Specifically, we take the perspective of a British, Japanese, Swiss, Canadian, and Australian investor. In any case, we find that our Taylor rule models render strong economic value regardless of the base currency and the Taylor rule specification.

## VI. Conclusion

In this article, we examine the cross-sectional predictive ability of forward-looking Taylor Rule models to generate economically meaningful and statistically significant trading returns in a currency portfolio context. Specifically, we construct trading signals that follow a Taylor rule strategy that incorporates the gap of inflation expectations and output from their targets. We show that a strategy that goes long high implied interest rate currencies and short low implied rate currencies offers highly positive and significant currency excess returns. Our Taylor rule signals are orthogonal to the information that is already priced in nominal interest rates and thus the corresponding spread portfolios exhibit very low correlations with currency carry trade strategies.

In addition, we show that existing currency investment strategies, such as carry trade, momentum, and value strategies are unrelated to the Taylor rule portfolios and they are not able to explain their cross-sectional variation. Only the Taylor rule portfolio demonstrates strong pricing ability for such test assets as well as a broader cross-section of currency investment strategies that include carry trade, inflation, output gap, momentum, value, and Taylor rule portfolios. Furthermore, the Taylor rule portfolio exhibits strong predictive power for the cross-section of carry trade and momentum portfolios.

We also evaluate the performance of other currency risk factors such as global foreign exchange market volatility, global foreign exchange market illiquidity, global risk aversion, and global political risk, and show that only global political risk is priced in the cross-section of Taylor rule portfolios. We also construct backward-looking Taylor rule models and show that they offer lower but statistically significant returns. However, forward-looking Taylor rule models obtain highly positive and significant alphas even after controlling for backward-looking Taylor rule models or carry trade portfolios, implying that they provide marginal information that it is not embedded in such strategies.

Our results are robust to a large number of robustness checks. Specifically, we show that the performance of the forward-looking Taylor rule portfolios is not affected by the proxy of output gap (i.e., unemployment gap or detrended industrial production), the method used to estimate the trend component of output, or the consideration of transaction costs. In addition, we show that the returns of the strategy are not subject to data snooping and survive a number of filters which ensure tradability. We also demonstrate that the results are robust to longer horizons of inflation forecasts and after taking the perspective of foreign investors.

In addition to demonstrating that our results are robust to data snooping tests, we do not find evidence of mispricing. On the other hand, we show that the forward-looking Taylor rule factor loadings exhibit strong predictability for currency returns, consistent with investors requiring a risk premium for holding currencies with high implied interest rates while currencies with low implied interest rates offer lower returns as they provide a hedge in the bad state of the world when high implied interest rate currencies drop in value. Thus, the profitability of the Taylor rule foreign exchange rate trading strategies probably largely reflect risk premia.

## Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022000771.

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