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Out-of-sample exchange rate predictability in emerging markets: Fundamentals versus technical analysis ☆

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ABSTRACT

We provide an in-depth analysis of the predictive ability of models with fundamentals and technical indicators for fourteen emerging market currencies. Our findings suggest that the forecasts from the symmetric Taylor rule as well as from a predictive regression exploiting the informational content of the momentum indicator are statistically superior to those of the random walk and other competing models. We combine the forecasts from the two best performing models via simple techniques and assess the economic significance of the out-of-sample forecasts using a trading strategy based on the sign of the predicted currency returns. Our economic significance results demonstrate that the symmetric Taylor rule, momentum and combination forecasts generate the largest net-of-transactions costs and risk-adjusted returns.

1. Introduction

Predicting exchange rate movements is undoubtedly a daunting task. Despite the inherent challenges in exchange rate prediction, obtaining accurate forecasts of exchange rate changes is of paramount importance to traders, policymakers and academics. From the perspective of policymakers in emerging markets, in particular, existing research (Gaies et al., 2018,2019, Sweeney, 1986) which associates the occurrence of banking crises to exchange rate stability underscores the centrality of understanding the drivers currency fluctuations and generating accurate exchange rate forecasts.

A number of anomalies, which characterize the state of international finance, exacerbate the difficulty in predicting exchange rate movements using macroeconomic fundamentals. On one hand, the 'exchange rate disconnect' puzzle

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establishes a 'disconnect' between macroeconomic (and monetary) fundamentals and exchange rate movements. This, in turn, implies that exploiting the informational content of fundamentals does not yield forecast improvements vis-à-vis the random walk (Meese and Rogoff, 1983; Bacchetta and van Wincoop, 2006; Cheung et al., 2005).[2] On the other hand, the existing literature provides ample evidence against Uncovered Interest Parity (UIP).[3]

Recent research, however, provides compelling evidence on the predictive power of fundamentals at short horizons (Engel et al., 2007; Molodtsova and Papell, 2009; Li et al., 2015). In line with the evidence on the predictive ability of fundamentals at short horizons, the sizeable literature on the use of technical analysis in the foreign exchange market also points to some success of technical trading rules in generating profits (Gençay, 1999; LeBaron, 1999; Neely and Weller, 2013; Raza et al., 2014). Nonetheless, the profitability from trading based on technical trading rules appears to be diminishing (Neely and Weller, 2003; Neely et al., 1997; Pukthuanthong et al., 2007).[4]

Academic researchers have, with the notable exceptions of de Zwart et al. (2009) and Buncic and Piras (2016), commonly examined fundamental and technical information in isolation whereas currency traders have been keen to use technical trading in the foreign exchange market with potentially little regard to the informational content of fundamentals (Menkhoff and Taylor, 2007).[5] Taking stock of the existing literature demonstrates that the evidence on the out-of-sample predictability of the exchange rate changes of emerging markets currencies using models with fundamentals continues to be lacking. Also absent from the literature is a systematic comparison of the out-of-sample predictive performance of the major exchange rate determination *models* and technical trading signals for emerging markets currencies as well as an assessment of the benefits of combining information from fundamentals and technical indicators for predicting and trading emerging markets currencies.

This paper attempts to fill the latter gaps and, by doing so, contributes to the literature along several lines. This paper is, to the best of our knowledge, the first to compare the out-of-sample predictive ability of the major *models* of exchange rate determination and technical indicators for emerging market currencies. Second, while existing research examines the profitability of cross-sectional momentum (Chong and Ip, 2009; Tajaddini and Crack, 2012) and other technical trading strategies (de Zwart et al., 2009) for emerging markets currencies, this study is the first to evaluate the *out-of-sample* predictive power and profitability of time series momentum indicators for individual emerging markets currencies.[6] Third, this study is among a few (Buncic and Piras, 2016; de Zwart et al., 2009) to offer an assessment of the advantages of combining fundamental and technical information for predicting and trading emerging markets currencies.

Compared to developed market currencies, emerging markets currencies may provide better profit opportunities because they have lower turnover (Bank of International Settlements, 2016), lesser competition among traders, and more easily identifiable trends (Frankel and Poonawala, 2010).[7] The latter view is validated in several studies which provide evidence that the returns to technical trading rules have diminished over time for the currencies of developed countries (Neely et al., 1997; Pukthuanthong et al., 2007; Pukthuanthong-Le and Thomas, 2008) and possibly migrated to emerging countries (Hsu et al., 2016; Chong and Ip, 2009; de Zwart et al., 2009; Tajaddini and Crack, 2012). We draw insight from this literature to examine the out-of-sample predictive ability of an exhaustive set of technical indicators. The technical trading rules that we consider are moving average, momentum and relative strength indicators.

We assess the out-of-sample forecast accuracy of the models with fundamentals and technical indicators using statistical and economic criteria. More specifically, we employ state of the art forecast accuracy statistics and tests to detect superior out-of-sample predictive ability relative to the random walk. We evaluate the profitability of trading currencies based on the sign of out-of-sample forecasts using a simple trading strategy according to which the investor is assumed to take a long (short) in the foreign currency if the predicted out-of-sample return is positive (negative). In contrast to the statistical evaluation, which we undertake at the individual currency level, our economic significance assessment, which carefully accounts for transaction costs, is performed at the individual currency and portfolio levels.

Our findings indicate that the symmetric Taylor rule, momentum indicator and the combination forecasts are statistically and economically superior to the random walk. From an economic significance perspective, trading individual currencies or forming portfolios based on the sign of the predicted return from the Taylor rule and the predictive regression with the momentum indicator as an independent variable generates statistically and economically significant risk-adjusted and net-of-transaction cost returns that exceed those of the competing models.

[2] Since the seminal contribution of Meese and Rogoff (1983), existing studies compare the statistical forecast accuracy of a model to that of the random walk.

[3] The absence of empirical support for UIP, according to which exchange rate changes should be equal to the interest rate differential between two countries, is closely connected to the 'forward premium puzzle' which is a another widely researched anomaly in international finance. Under risk neutrality and rational expectations, one of the implications of UIP is that the forward rate is an unbiased predictor of the future spot rate (Li et al., 2015). Nonetheless, the considerable evidence on the 'forward premium puzzle' for the currencies of developed economies implies that forward rates are biased predictors of the future spot rate. For comprehensive reviews of the forward premium anomaly literature, see Engel (1996, 2015).

[4] See Rossi (2013) for a critical review of the literature on exchange rate predictability with fundamentals and Park and Irwin (2007) for a survey on the profitability of technical trading rules in the foreign exchange and other markets.

[5] In fact, de Zwart et al. (2009) assess the predictive ability of fundamental and technical indicators for emerging market currencies while Buncic and Piras (2016) examine the out-of-sample predictive ability of technical indicators and risk measures for six exchange rate changes of developed economies.

[6] Consistent with the arguments in Qi and Wu (2006), an out-of-sample assessment provides a more stringent test of the profitability of technical trading rules and eliminates data snooping biases.

[7] For example, Frankel and Poonawala (2010) assert that "Emerging market currencies probably have more easily-identified trends of depreciation than currencies of advanced countries".

The remainder of the paper is organized as follows. Our data and variables are presented in Section 2. Section 3 outlines the models with fundamentals and the technical trading indicators which we employ to predict currency returns. Sections 4 and 5 present the statistical and economical evaluation methods, respectively. Section 6 reports and discusses our in sample and out-of-sample forecasting results. Section 7 offers some concluding remarks.

2. Data and variables

2.1. Spot and one-month forward rates

We collect the WMR/Reuters spot and one-month forward exchange rates for a cross-section of fourteen currencies against the United States Dollar (USD) from Datastream. The forward and spot rates are expressed in USD per unit of the foreign currency (or domestic price of a foreign currency unit). More specifically, our cross-section comprises the following currencies: the Mexican New Peso (MXN), Hong Kong Dollar (HKD), Indian Rupee (INR), Indonesian Rupiah (IDR), Philippine Peso (PHP), Kuwaiti Dinar (KWD), New Taiwan Dollar (TWD), Saudi Riyal (SAR), Singapore Dollar (SGD), Thai Baht (THB), Czech Koruna (CZK), Hungarian Forint (HUF), South African Rand (ZAR) and the New Turkish Lira (TRY).

Of the latter countries, three are classified by the World Bank as lower-middle-income economies (India, Indonesia and Philippines), four are classified as upper-middle-income economies (Mexico, South Africa, Thailand and Turkey) and seven are high-income-economies (Hong Kong, Hungary, Taiwan, Kuwait, Saudi Arabia, Singapore and Czech Republic).[8] For simplicity, we refer to all of the latter fourteen countries as emerging markets and to their currencies as emerging markets currencies. The latter classification is broadly consistent with that of the International Monetary Fund (2015).[9] Our cross-section of emerging markets currencies as well as our sample start date of December 1996 are identical to those of Frankel and Poonawala (2010). We do not expand our cross-section of emerging market currencies beyond that of Frankel and Poonawala (2010) given the unavailability of one-month forwards for the other emerging markets currencies starting in December 1996.[10]

It is also important to note that, as discussed in de Zwart et al. (2009), our sample start date corresponds to a floating exchange rate regime for most of the emerging markets currencies. Hong Kong, Thailand, and Saudi Arabia are exceptions since these emerging market countries have pegged their currencies to the USD over part of (or the entire) sample period.[11] Nonetheless, we elect to keep these currencies so that our cross-section is identical to that of Frankel and Poonawala (2010).

In line with Frankel and Poonawala (2010), we employ deliverable one-month forwards in our analysis. We acknowledge that some of the emerging market countries in our cross-section, such as Taiwan, India and the Philippines, have non-deliverable forwards. In addition, we acknowledge that Indonesia and Thailand introduced capital controls in 2000 and 2007, respectively, making their forwards, which used to be deliverable prior to these dates, non-deliverable (de Zwart et al., 2009). Despite these caveats, we should note, as discussed next, that we use the deliverable forwards to generate forecasts only from a single model (which is the Uncovered Interest Parity model) and that our trading strategy assumes that the investor can transact in the spot, rather than the forward, market. In order to benchmark our results against those of influential studies in the literature (Della Corte and Tsiakas, 2012; Li et al., 2015; Lustig et al., 2011; Daniel et al., 2017; Bekaert and Panayotov, 2017), we also provide results for the ten most liquid currencies of advanced economies (i.e., the G10) in an online appendix to conserve space.

Our data spans the period from December 1996 to June 2017. Our starting date is dictated by the availability of one-month forward rate data for the emerging market currencies while our sample is constrained to end in June 2017 given that Gross Domestic Product (GDP) (see section 2.2) data are available with a time lag. The monthly spot and one-month forward quotes are sampled from daily data as the last observation of the month. The return on currency i in month t is given by: $\Delta s_{it} = \ln(S_{it}) - \ln(S_{it-1}) = s_{it} - s_{it-1}$ for $i = 1, 2, \cdots, 14$ where S_{it} denotes the exchange rate expressed in terms of USD price of a unit of the foreign currency.

2.2. Macroeconomic data

We obtain macroeconomic data for the fourteen countries comprising our cross-section from Datastream. More specifically, estimation and prediction from the models with fundamentals requires data on (real) Gross Domestic Product (GDP), inflation and the money supply for each of the countries. We collect data on the seasonally adjusted real GDP, non-seasonally

[8] The World Bank classification is available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[9] See, for example, Table A.6 and A.7 on pages 176–178 of the International Monetary Fund (2015)'s World Economic Outlook. Admittedly, our classification is a little loose. The International Monetary Fund classifies Hong Kong and Singapore as advanced economies.

[10] For example, one-month forward data on the Argentine and Chilean Pesos begin in 2004 while data on the Chinese Yuan start in 2002. This does not leave us with sufficient observations for in-sample estimation of the models. In contrast, starting the analysis in December 1996 leaves us with a sufficiently long history to undertake a forecasting exercise.

[11] While including HKD, THB and SAR in our cross-section does not affect the individual currency out-of-sample forecasting results for the other emerging market currencies, it will affect the results of our assessment of economic significance using portfolios that we discuss in Section 6.2. We assess the robustness of our portfolio results by excluding these currencies from the analysis and our results are qualitatively similar to when we include these currencies. These results are available from the authors.

adjusted M1 as a measure of the money supply and the Consumer Price Index (CPI) for each of the countries. The money supply data are collected by the countries' central banks while the source of the GDP and CPI data are the national statistical agencies of each of the countries.

Following Della Corte and Tsiakas (2012), we deseasonalize M1 by implementing the procedure of Gomez and Maravall (2000). We also use Gomez and Maravall (2000)'s approach to seasonally adjust the CPI for each country. Given that GDP is only available at the quarterly frequency (for all the countries), we linearly interpolate the GDP series to obtain data at the monthly frequency using the Chow and Lin (1971) procedure. GDP and M1 figures are then converted into USD using the spot exchange rate. Table 1 presents the summary statistics of the exchange rates and predictors. In line with the stylized facts discussed in the literature (Gospodinov, 2009), the volatility of the currency returns is significantly larger than that of the forward premium. In addition, there is considerable dispersion in the differences in inflation, output growth and money supply growth among the countries in our cross-section.

We should highlight some important data gaps. Data on the CPI are not available for India and Kuwait. In addition, GDP data are not available for India, while they are available for Indonesia only starting 2011 and for Philippines and Turkey only starting 1998. The money supply data for Thailand are available only starting November 2015 and starting December 2005 for Turkey. In light of these data constraints, we are unable to estimate and predict from some of the models with fundamentals for these currencies.

3. Econometric methodology

3.1. The predictive power of fundamentals

Similar to Della Corte and Tsiakas (2012), most of our predictive models are cast within the general framework of a predictive regression. The simple predictive regression is given by:

$$\Delta s_{it+1} = \alpha + \beta x_{it} + \varepsilon_{it+1} \tag{1}$$

where x_{it} denotes one of the fundamental predictors. When predicting from the models with fundamentals, we only include information that is available in traders' information set at the time the forecast is generated. That is, we follow de Zwart et al. (2009) by using the sixth lag of x_{it} whenever the macroeconomic data are included in the model to account for the delays in the release of, and revisions to, macroeconomic data in the emerging market economies. We provide next an overview of each of the models that we employ. The exposition we adopt follows Della Corte and Tsiakas (2012) closely.

3.1.1. Random walk with drift

The first model that we consider is the random walk with drift. Since the seminal contribution of Meese and Rogoff (1983), the random walk constitutes the benchmark against which the statistical accuracy of exchange rate forecasting models is assessed. As Della Corte and Tsiakas (2012) note, imposing $\beta = 0$ yields the random walk with drift model under which $\Delta s_{it+1} = \alpha + \epsilon_{it+1}$.

The random walk with drift benchmark that is used to assess the relative predictive ability of models in the currency return prediction literature is equivalent to the historical average that is widely employed as a benchmark in the equity return prediction literature (Welch and Goyal, 2008; Neely et al., 2014).

3.1.2. Uncovered and covered interest parity

Uncovered Interest Rate Parity (UIP) is one of the most researched hypotheses in modern international finance. Under the assumptions that agents are risk-neutral and form rational expectations, UIP postulates that exchange rate changes are equal to the interest rate differential between two economies (Sarno and Taylor, 2002). More formally, let i_t and i_t^* denote the nominal interest rates on comparable domestic and foreign securities, respectively. If UIP holds, the change in the exchange rate should be equal to the interest rate differential $\Delta s_{t+1} = i_t - i_t^*$. UIP can be tested using the predictive regression $\Delta s_{t+1} = \alpha + \beta(i_t - i_t^*) + \vartheta_{t+1}$. If UIP holds, the null hypothesis $H_0 : \alpha = 0, \beta = 1$ cannot be rejected. The UIP hypothesis can also be tested indirectly by imposing Covered Interest Parity (CIP), which stipulates that the interest rate differential between the two currencies is equal to the forward premium. More formally, the CIP hypothesis is given, in logarithmic form, by $f_t - s_t = i_t - i_t^*$ where $f_t = \ln(F_t)$ is the logarithm of the one-month forward rate and $f_t - s_t$ is the forward premium (or discount). Unlike UIP, which is a predictive relation, CIP is a contemporaneous arbitrage relation with ample empirical support.[12] When combined with CIP, UIP can be tested via the Fama (1984) regression:[13]

$$x_{it} = f_{it} - s_{it}. \tag{2}$$

[12] CIP is typically tested using the regression $f_t - s_t = \alpha + \beta(i_t - i_t^*) + \epsilon_t$. If CIP holds, the null hypothesis $H_0 : \alpha = 0, \beta = 1$ should not be rejected. For studies providing empirical support for at high frequencies prior to the financial crisis see, for example, Akram et al. (2008) and Fong et al. (2010). Recent contributions to the literature provide evidence of short-lived deviations from CIP during and after the financial crisis (Baba and Packer, 2009; Du et al., 2017; Borio et al.,2016; Mancini-Griffoli and Ranaldo, 2011).

[13] Studies which use the Fama (1984) approach include Froot and Thaler (1990), Baillie and Bollerslev (1989,2000), Bansal and Dahlquist (2000), Frankel and Poonawala (2010) and Ahmad et al. (2012).

Table 1
Descriptive statistics. This table reports summary statistics for the exchange rate returns, Δs_{t+1}, the forward premium, $f_t - s_t$, differences in inflation, $\Delta(p_t - p_t^*)$, differences in the growth of the money supply, $\Delta(m_t - m_t^*)$, and differences in the growth of real Gross Domestic product, $\Delta(y_t - y_t^*)$, for a cross-section of nine fourteen emerging markets. The sample period is December 1996 to June 2017.

	Δs_{t+1}		$f_t - s_t$		$\Delta(p_t - p_t^*)$		$\Delta(m_t - m_t^*)$		$\Delta(y_t - y_t^*)$	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
CZK	0.067	3.592	−0.071	0.338	0.385	2.337	−0.207	3.747	0.022	0.758
HKD	−0.003	0.120	0.006	0.108	0.466	2.829	−0.501	7.040	−0.080	0.577
HUF	−0.217	3.894	−0.438	0.313	−3.579	4.168	−0.362	3.800	−0.011	0.303
IDR	−0.703	7.403	−2.020	4.491	−7.049	10.502	−0.067	6.704	–	–
INR	−0.240	2.037	−0.391	0.232	–	–	−0.286	3.453	–	–
KWD	−0.006	0.706	−0.053	0.099	–	–	−0.355	3.964	–	–
MXN	−0.335	2.904	−0.588	0.500	−4.141	4.779	−0.358	3.076	−0.017	0.356
PHP	−0.264	2.445	−0.332	0.310	−2.336	1.980	−0.387	3.053	−0.220	0.395
SAR	0.000	0.086	−0.012	0.052	−0.455	3.073	−0.399	1.780	–	–
SGD	0.007	1.780	0.059	0.128	0.600	1.845	−0.302	2.439	−0.214	0.825
THB	−0.115	3.176	−0.191	0.420	−0.367	1.931	–	–	–	–
TRY	−1.432	4.663	0.448	12.421	−19.198	19.739	−0.025	4.358	−0.174	4.483
TWD	−0.041	1.593	0.072	0.263	1.149	1.254	−0.054	2.363	−0.131	0.651
ZAR	−0.423	4.573	−0.589	0.237	−3.640	2.571	−0.074	5.104	−0.031	0.277

Under UIP, the null hypothesis $H_0 : \alpha = 0, \beta = 1$ is not rejected.

Li et al. (2015) note that the implications of rejecting UIP are twofold. The first is that the forward rate is a biased predictor of the future spot rate. The sizeable literature on the forward premium anomaly for developed currencies provides empirical evidence that confirms that the forward rate is a biased predictor of the future spot rate. While the forward premium anomaly is a staple of developed market currencies, existing research (Bansal and Dahlquist, 2000; Frankel and Poonawala, 2010) suggests that the forward premium puzzle is much less pronounced for the currencies of emerging markets. This, in turn, implies that while the forward rate may still be a biased predictor of future exchange rate movements of emerging markets, it might indicate the correct directional change in the exchange rate movements (Frankel and Poonawala, 2010).[14] This potentially makes the forward rate a useful predictor of the future spot rate.[15] Indeed, further credence for the latter conjecture is offered by Gilmore and Hayashi (2011) who, using a cross-section of emerging markets spot and forward exchange rates, provide empirical evidence that assuming a long position in high forward premium currencies increases portfolio returns.

3.1.3. Purchasing power parity

A Purchasing Power Parity (PPP) exchange rate guarantees that a unit of the currency has the same purchasing power in two economies (Sarno and Taylor, 2002).[16] As Mark (2001) notes, the commodity-arbitrage view of PPP in Samuelson (1964) requires that the Law of One Price holds for tradeable goods. The PPP hypothesis can be tested using the following regression:

$$x_{it} = p_t - p_{it}^* - s_{it}, \tag{3}$$

where p_t and p_t^* denote, respectively, the logarithm of the domestic and foreign price levels.

While PPP is commonly viewed as a long-run condition, existing studies (Della Corte and Tsiakas, 2012; Li et al., 2015) explore its short-run predictive performance for the developed market currencies. The findings emerging from the literature cast doubt on the predictive ability of PPP. In the context of emerging markets, Taylor and Taylor (2004) provide evidence of long-lived deviations from PPP. This is likely to translate into a weak predictive performance of PPP for the emerging market currencies.

3.1.4. Monetary fundamentals

International macroeconomic models postulate that nominal exchange rate movements are driven by macroeconomic fundamentals. More specifically, the Monetary Fundamentals (MF) model is given by:

$$x_{it} = (m_t - m_{it}^*) - (y_t - y_{it}^*) - s_{it}, \tag{4}$$

where m_t and m_t^* denote, respectively, the logarithms of the domestic and foreign money supply and y_t and y_t^* are, respectively, the natural logarithms of the domestic and foreign national income.

[14] It is interesting to note that Bansal and Dahlquist (2000) relate the attenuation of the forward premium puzzle for emerging market economies to macroeconomic fundamentals such as per capita GNP, average inflation rates and inflation volatility. This implies that fundamentals might possess predictive power for the exchange rate changes of emerging market economies.

[15] In fact, the basis, whose construction is almost identical to the forward premium, is a good predictor in the energy (Alquist and Kilian, 2010; Chinn and Coibion, 2014; Gospodinov and Ng, 2013), agricultural (Chinn and Coibion, 2014) and interest rate (Gospodinov and Jamali, 2011) markets.

[16] Another definition of a PPP exchange rate is one which "would equate the two relevant national price levels if expressed in a common currency" (Sarno and Taylor, 2002).

Existing research documents a feeble link (Sarno and Sojli, 2009) between exchange rate movements and fundamentals. Several explanations have been offered for the weak relation between fundamentals and exchange rate returns. Engel and West (2005) show analytically that the disconnect between fundamentals and exchange rates can be driven by a discount factor that is close to unity. Sarno and Sojli (2009) provide empirical evidence that the discount rate is close to one and thereby support Engel and West (2005)'s analytical account. Another explanation for the disconnect between fundamentals and exchange rates is offered by Sarno and Valente (2009) who argue that the relationship between fundamentals and exchange rates is shifting across time.[17] Despite that monetary fundamentals do not exhibit predictive power for the developed currencies, the existing studies do not explore the predictive power of monetary fundamentals for the emerging market currencies.

3.1.5. Taylor rule

In an important contribution to the literature, Taylor (1993) introduced a rule, subsequently dubbed the Taylor rule, which posits that the monetary authority's policy on interest rates is a function of the difference between inflation and target inflation as well as the output gap defined as the difference between output and a measure of potential output.

Molodtsova and Papell (2009) devise an open economy version of the Taylor rule which they employ for exchange rate forecasting. To derive an open economy version of the rule, Molodtsova and Papell (2009) assume that the central banks in the home and foreign countries set the short-term nominal interest rates according to the Taylor rule. The authors then subtract one Taylor rule from the other to obtain an open economy variant of the Taylor rule in which the interest rate differential between the two countries is a function of the inflation differential and the output gap. Assuming that UIP holds, Molodtsova and Papell (2009) replace the interest rate differential by the exchange rate change and this yields the following symmetric Taylor rule (TR_s):

$$\Delta s_{it+1} = \alpha + \theta(\pi_t - \pi_{it}^*) + \gamma(y_t^g - y_{it}^{*g}) + \epsilon_{it+1} \tag{5}$$

where π_t is domestic inflation, π_t^* is the foreign inflation rate and y_t^g and y_{it}^{*g} are the domestic output and foreign output gaps, respectively. The domestic and foreign output gaps are defined, consistent with the existing literature, as the deviation between real output and an estimate of potential output. Following the existing literature (Della Corte and Tsiakas, 2012; Li et al., 2015; Molodtsova and Papell, 2009), we estimate potential output using the Hodrick and Prescott (1997) filter and define the output gap as a percent deviation of real output from its potential.[18] Unlike our previous models, which are simple predictive regressions, the Taylor rule is a multiple linear regression. While the existing literature (Della Corte and Tsiakas, 2012; Engel et al., 2007) fixes (or calibrates) the parameters of the Taylor rule, we estimate the parameters in view of the significant heterogeneity among the countries in our cross-section.[19]

Another variant of the Taylor rule, referred to as the asymmetric Taylor rule, can be obtained by assuming that one or both central banks target the PPP level of the exchange rate (Molodtsova and Papell, 2009). In an asymmetric Taylor rule (TR_a), the real exchange rate appears as an additional predictor:

$$\Delta s_{it+1} = \alpha + \theta(\pi_t - \pi_{it}^*) + \gamma(y_t^g - y_{it}^{*g}) + \delta(p_t - p_{it}^* - s_t) + u_{it+1} \tag{6}$$

Again, the asymmetric Taylor rule is a multiple linear regression and is therefore nested within the framework of the simple linear regression in Eq. (1) under two exclusion restrictions (i.e., restricting two coefficients in Eq. (6) to zero).

3.2. The technical approach

As noted earlier, several studies examine the profitability of technical trading (Gençay, 1999; LeBaron, 1999; Neely and Weller, 2013; Raza et al., 2014) in the context of foreign exchange markets. In this section, we closely follow the approach of Neely et al. (2014) to study the predictive power of technical trading signals for the currencies of emerging markets. Neely et al. (2014) generate point forecasts from a predictive regression in which the technical trading signal is an indicator variable. Doing so allows for comparing the forecasts of the predictive regressions with fundamentals and technical indicators. The predicted currency return is obtained from:

$$\Delta s_{it+1} = \alpha + \beta z_{it} + v_{it+1} \tag{7}$$

where z_{it} is an indicator variable that takes the value one for a buy (i.e., bullish) signal and a value of zero for a sell (i.e., bearish) signal ($z_{it} = 1$ and $z_{it} = 0$, respectively). We employ three popular technical indicators whose effectiveness is explored by

[17] Yet another potential explanation for the feeble link between fundamentals and exchange rate changes is nonlinearities. Sarno et al. (2006) provide evidence of nonlinearities in UIP, for example.

[18] Following existing studies (Della Corte and Tsiakas, 2012; Li et al., 2015; Molodtsova and Papell, 2009), the smoothing parameter is set to 14,400. When performing out-of-sample forecasting, we follow Della Corte and Tsiakas (2012) and Li et al. (2015) by estimating the Hodrick and Prescott (1997) trend, at any time t, using information up to t-1. The trend is updated every time a new observation becomes available. Della Corte and Tsiakas (2012) and Li et al. (2015) note that the latter approach mimics as closely as possible a central bank's information set at time t and thereby limits look-ahead bias.

[19] Engel et al. (2007) provide a discussion of the rationale underlying the choice of the parameters in the Taylor rule. Li et al. (2015) find that fixing or estimating the parameters of a Taylor rule yields qualitatively similar results.

Neely et al. (2014) in the context of equity markets. These indicators are the simple moving average, momentum and relative strength index. We provide next details on each of these indicators.

3.2.1. The moving average indicator

Moving average (MA) rules are the most popular technical trading rules. To generate a trading signal from the MA indicator, we compute a simple MA of the spot exchange rates over the past j months $MA_t = 1/j\sum_{i=0}^{j-1}S_{t-i}$ for each currency pair, for $j = s, l$, where $s(l)$ is the length of the short (long) MA ($s < l$). An upward (downward) trend is usually identified when the short moving average $(MA_{s,t})$is greater (less) than the long moving average $(MA_{l,t})$. Monthly buy and sell signals are thus defined as:

$$MA\ \ Trading\ \ Signals = \left\{ \begin{array}{ll} z_t^{MA} = 1, & if\ \ MA_{s,t} \geq MA_{l,t}(Buy\ \ Signal) \\ z_t^{MA} = 0, & if\ \ MA_{s,t} < MA_{l,t}, (Sell\ \ Signal) \end{array} \right\}. \tag{8}$$

Recent research (Levine and Pedersen, 2016) provides evidence that MA rules are capable of capturing time series momentum in asset prices. Following Neely et al. (2014), we analyze six monthly MA rules (1,9), (1,12), (2,9), (2,12), (3,9), and (3,12).

3.2.2. The momentum indicator

Momentum (MOM) is another popular investing style among technicians that is predicated on the belief that trends in asset prices tend to persist.[20] Technicians attempt to detect and exploit the existence of such trends to generate abnormal profits. Existing research documents the success of cross-sectional (Jegadeesh and Titman, 1993; Carhart, 1997) and time series momentum (Moskowitz et al., 2012) in generating superior returns to equity investors. Momentum investing has also been found to be an effective trading strategy within the context of the foreign exchange market (Menkhoff and Taylor, 2007; Menkhoff et al., 2012; Raza et al., 2014; Hsu et al., 2016).

To explore the effectiveness of momentum signals for individual currencies, we follow Neely et al. (2014) by generating momentum signals, which compare the exchange rate in month t to the exchange rate m months ago. More specifically, the buy and sell signals are generated as follows:

$$MOM\ \ Trading\ \ Signals = \left\{ \begin{array}{ll} z_t^{MOM} = 1, & if\ \ S_t \geq S_{t-m} \\ z_t^{MOM} = 0, & if\ \ S_t < S_{t-m} \end{array} \right\}. \tag{9}$$

Also in line with Neely et al. (2014) we investigate the profitability of two momentum indicators corresponding to m = 9, 12 which we refer to as MOM (9) and MOM (12).

3.2.3. The relative strength index

Unlike the moving average and momentum indicators, which are trend-following indicators, the Relative Strength Index (RSI) is a contrarian indicator whose aim is to identify periods in which a currency is overbought (i.e., expensive) or oversold (i.e., inexpensive). More specifically, when the RSI, also referred to as an oscillator, breaches certain thresholds, a price correction is considered to be imminent (Hsu et al., 2016). The RSI is computed from the average gains and losses over the previous fourteen months.[21]

Following existing studies (Buncic and Piras, 2016; Hsu et al., 2016), the two thresholds that we employ to evaluate whether a currency is overbought or oversold are 70 and 30, respectively. When the RSI dips below 30, this indicates that the downward trend is likely to reverse and suggests a bullish (or buy) signal given that the support level for the price has been or is almost breached. On the converse, an increase in the RSI above 70 indicates that the resistance level has been breached. This, in turn, is considered to be a bearish (or sell) signal. Buy and sell signals are therefore defined as:

$$RSI\ \ Trading\ \ Signals = \left\{ \begin{array}{l} z_t^{RSI} = 1, if\ \ RSI_t \leq 30 \\ z_t^{RSI} = 0, if\ \ RSI_t \geq 70 \end{array} \right\}. \tag{10}$$

We assume that the buy (sell) position is maintained until the RSI indicates that it should be reversed.

4. Statistical evaluation of forecast accuracy

We delineate our full sample into an in-sample (IS) and out-of-sample (OOS) periods. The IS period is employed to estimate the models via Ordinary Least Squares (OLS) while the OOS period is preserved to evaluate the statistical accuracy of the competing models.

[20] In fact, a well-known mantra amongst technicians is that "the trend is your friend".

[21] More specifically, we first calculate the monthly relative strength RS measured as the ratio of total average gains to total average losses ($RS = Av.Gains/Av.Losses$) for each currency. Average gains (losses) are calculated by cumulating gains (losses) from the past fourteen months and dividing by fourteen. The monthly gain (loss) is determined by whether the spot rate in the current month is higher (lower) than that of the previous month. The RS is then converted into an index that ranges between 0 and 100 using the following equation: $RSI = 100 - [100/(1 + RS)]$.

Starting from exchange rate returns, fundamental and technical predictors denoted respectively by $\Delta s_{t+1}, x_t$ and z_t, we follow Della Corte and Tsiakas (2012) by dividing our full sample period, $t = 1$ to $t = T - 1$, into an IS period spanning observations $t = 1$ to $t = M$ and an OOS period spanning observations $t = M + 1$ to $t = T - 1$. This results in $P = (T - 1)\text{-}M$ out-of-sample forecasts. Our full sample period extends from December 1996 to June 2017 (accounting for the lost observation to construct the returns) so that $T - 1 = 248$. Our OOS period is September 2008 to June 2017 so that $P = 106$ and $M = 142$. We generate rolling one-step-ahead forecasts from the competing models over the OOS period.

We reemphasize the fact that, as in de Zwart et al. (2009), we use the sixth lag of the predictors when generating forecasts from the PPP, MF, TR_s and TR_a so as to only incorporate information that is available in traders' information sets at the time the forecasts are generated. In contrast, when we predict the currency returns from the UIP model, we use the forward premium at time t-1 to predict returns at time t given that forward and spot rates are readily available to market participants.

Our assessment of the statistical forecast accuracy of the competing models begins with the OOS R^2 which is widely used in the equity (Campbell and Thompson, 2007; Welch and Goyal, 2008, Maio, 2014; Rapach et al., 2010) and the foreign exchange prediction literatures (Anatolyev et al., 2017; Della Corte and Tsiakas, 2012; Li et al., 2015). Under quadratic loss, the OOS R^2 is computed as:

$$R^2_{oos} = 1 - \frac{\sum_{t=M+1}^{T-1}\left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)^2}{\sum_{t=M+1}^{T-1}\left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)^2} = 1 - \frac{\sum_{t=M+1}^{T-1}L\left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)}{\sum_{t=M+1}^{T-1}L\left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)}, \tag{11}$$

where $\Delta\widehat{s}_{t+1}$ is the rolling one-step-ahead forecast from one of the competing models, $\Delta\bar{s}_{t+1}$ is the random walk (with drift) benchmark forecast and $L(.)$ denotes the quadratic loss function. The R^2_{oos} can also be expressed in terms of the loss function, $L(.)$, which is a function of the forecast errors. A positive (negative) R^2_{oos} indicates that the model outperforms (underperforms) the benchmark.

In order to test the statistical significance of the differences in Mean Squared Errors (MSEs) between the competing models and the random walk benchmark, we employ the *MSE-F* statistic of McCracken (2007):

$$MSE - F = \frac{\sum_{t=M+1}^{T-1}\left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)^2 - \left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)^2}{\sum_{t=M+1}^{T-1}\left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)^2} \tag{12}$$

As noted in Della Corte and Tsiakas (2012), the popular Diebold and Mariano (1995) and West (1996) statistics cannot be employed to assess the statistical significance of the differences in MSEs between a model and the random walk benchmark because the competing models nest the random walk benchmark (Clark and McCracken, 2001; Diebold, 2015).[22]

In addition to the *MSE-F* statistic, we assess the statistical accuracy of the competing models using the Clark and West (2007) test. The premise of Clark and West (2007)'s test is that estimating the parameters of the models will introduce estimation uncertainty without these parameters necessarily improving out-of-sample prediction. In fact, the MSE of the random walk can be lower than that of an estimated model because of the noise associated with estimating the parameters. This does not automatically imply, however, that the random walk outperforms the competing model in terms of out-of-sample forecast accuracy. In order to remedy the latter problem, Clark and West (2007) suggest employing the *adjusted* MSE:

$$MSE_{adj} = \frac{1}{P}\sum_{t=M+1}^{T-1}\left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)^2 - \frac{1}{P}\sum_{t=M+1}^{T-1}\left(\Delta\bar{s}_{t+1} - \Delta\widehat{s}_{t+1}\right)^2 \tag{13}$$

The test of equal MSEs is obtained as the t-statistic of a zero intercept in a regression of:

$$\widehat{f}_{t+1} = \left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)^2 - \left[\left(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}\right)^2 - \left(\Delta\bar{s}_{t+1} - \Delta\widehat{s}_{t+1}\right)^2\right] \tag{14}$$

on a constant. We refer to the latter test as CW. Clark and West (2006, 2007) show that the standard normal critical values are a good approximation to the critical values obtained from the non-standard asymptotic distribution of the CW test (Della Corte and Tsiakas, 2012). Therefore, we use the standard normal critical values when testing for differences in MSEs. Rapach et al. (2010) note that the CW test can be viewed as a test of the null $R^2_{oos} \leq 0$ against the alternative $R^2_{oos} > 0$.

The third test that we employ is the Giacomini and Rossi (2010) fluctuations test. Giacomini and Rossi (2010) note that forecasting models can exhibit significant instabilities. In fact, Rossi (2013) provides compelling evidence of instabilities in exchange rate forecasting models. The evidence of instability in exchange rate return prediction models motivates the use of the Giacomini and Rossi (2010) test.

Giacomini and Rossi (2010) propose a test that is adept at comparing equal predictive accuracy in unstable environments. The Giacomini and Rossi (2010) test statistic can be computed from the difference in loss functions over a rolling window of size m as:

[22] In fact, the random walk benchmark can be viewed as the restricted model whereas any of the competing models can be viewed as an unrestricted model. Let the *MSE* of the restricted and unrestricted model be denoted by MSE_R and MSE_U, respectively, the R^2_{oos} and *MSE-F* can be written as $R^2_{oos} = 1 - \frac{MSE_U}{MSE_R}$ and $MSE - F = P\frac{MSE_R - MSE_U}{MSE_U}$. For excellent reviews on the literature on testing for unconditional predictive ability, see Clark and McCracken (2010, 2013).

$$F^{OOS}_{t+1,m} = \widehat{\sigma}^{-1} m^{-1/2} \sum_{j=t-m}^{t} \Delta L_{t+1}, \quad t = M+1, \cdots, T-1, \tag{15}$$

where $\Delta L_{t+1} = L(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}) - L\left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)$ is the difference in the loss function between the competing model and the random walk benchmark and $\widehat{\sigma}^2$ is the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator of the long-run variance of the loss differences.

Under the null hypothesis, the two models under consideration exhibit equal predictive accuracy. When considering a one sided alternative, rejecting the null hypothesis implies that the competing model significantly outperforms the random walk benchmark. With a one sided alternative, the fluctuation test statistic is given by:

$$max_{t+1} F^{OOS}_{t+1,m} \tag{16}$$

When the fluctuation test statistic exceeds the one sided critical value, the competing model performs better than the random walk benchmark. We refer to the one-sided fluctuations test statistic in Eq. (16) by GR. The rolling window size we employ is $m = 60$.

While the prior tests are concerned with unconditional predictive ability, we also employ the Giacomini and White (2006), which is a test of conditional predictive ability, to assess the OOS forecasting performance of the competing models. More specifically, the Giacomini and White (2006), henceforth GW, test conditions on the agent's information set at time t Clark and McCracken (2013). The use of the GW test carries several advantages. First, our rolling window forecasting scheme lends itself directly to the use of the GW test. Second, the GW test allows for nested and non-nested model comparisons. Third, the GW test is not only a test of conditional predictive ability but also one of finite-sample predictive ability. That is, unlike tests which assume that that parameter estimation error vanishes asymptotically and replace estimates by their probability limits, the GW test preserves estimation uncertainty (Clark and McCracken, 2013; Elliott and Timmermann, 2016).

The GW test is based on the difference between the loss functions of one of the competing models and the random walk benchmark $\Delta L_{t+1} = L(\Delta s_{t+1} - \Delta\widehat{s}_{t+1}) - L\left(\Delta s_{t+1} - \Delta\bar{s}_{t+1}\right)$. Following Giacomini and White (2006), the test function is $(1, \Delta L_{t+1})'$. The GW test statistic follows the Chi-squared distribution with two degrees of freedom, χ^2_2, and the difference in the loss functions is significant if it exceeds the critical value. In line with the notation of Giacomini and White (2006), a GW statistic that is significant at the 10% level is succeeded by a (+) or (−) indicating that the model's forecast outperforms or underperforms the benchmark.

5. Economic evaluation of predictability

Existing research establishes that statistical forecast (in)accuracy need not automatically imply (lack of) profitability (Leitch and Tanner, 1991; Satchell and Timmermann, 1995). It is therefore natural to examine next the profitability of trading based on the fundamental and technical forecasts.

We do so using a simple trading strategy based on the sign of the predicted return from one of the models. The trading strategy assumes that the investor trades in the spot market and goes long currency i if the predicted return of currency $\underline{i}$ from model j is positive and short currency i when the predicted return of currency i from model j is negative:

$$Trading\ \ Strategy = \left\{ \begin{array}{l} buy\ \ if\ \ \Delta\widehat{s}_{ijt+1} > 0 \\ sell\ \ if\ \ \Delta\widehat{s}_{ijt+1} < 0 \end{array} \right\}. \tag{17}$$

The realized (gross) return from trading currency i based on model j's forecast is given by:

$$\Delta s^{realized}_{ijt+1} = sign\left(\Delta\widehat{s}_{tjt+1}\right) \times \Delta s_{it+1}. \tag{18}$$

The intuition behind our trading strategy is simple: The investor realizes a gain when the sign of the predicted currency return from model j is the same as that of the actual return while the investor records a loss otherwise.

Given that transaction costs can diminish or erode the profitability of a trading strategy, it is important to examine whether the profitability of a strategy persists after accounting for transaction costs. To do so, we calculate the net-of-transaction costs dynamic return, Δs^{net}_{itj+1}, by deducting the proportional transaction costs τ_{it+1} from the gross return:

$$\Delta s^{net}_{ijt+1} = \Delta s^{realized}_{ijt+1} - \tau_{it+1}. \tag{19}$$

The proportional transaction cost equals $\tau^{long}_{it+1} = ln(1 + c_{it}/1 - c_{it+1})$ for long positions, and $\tau^{short}_{it+1} = ln(1 - c_{it}/1 + c_{it+1})$ for short positions, where $c_{it+1} = \left(0.5\left(S^a_{it+1} - S^b_{it+1}\right)/S_{it+1}\right)$ is the one-way proportional transaction cost and S^a_t and S^b_t are, respectively, the ask and bid spot exchange rates. This approach to accounting for transaction costs has been used in several studies (Neely et al., 2009; Della Corte and Tsiakas, 2012; Li et al., 2015). We assess the economic value of exchange rate predictability for all the models with fundamental and technical indicators using the net-of-transaction costs dynamic return in Eq. (19).

We also assess the profitability of trading a basket of currencies based on the sign of the predicted return from the competing models by forming portfolios. At the portfolio level, the net-of-transaction cost realized return on a portfolio formed based on the sign of the predicted return from model j is an equally weighted average of the net realized return in Eq. (19). We compare the returns of the equally weighted portfolios of the technical and fundamentals models to three benchmark portfolios whose construction we discuss next.

6. Empirical results

6.1. Statistical evaluation

6.1.1. Full sample results

Our analysis of the predictive ability of fundamentals and technical indicators commences with the full sample estimation results of the predictive regressions in Eqs. (1)–(7) for the models with fundamentals and technical indicators. The estimation results for the models with fundamentals are presented in Table 2 while those of the predictive regressions with technical indicators are reported in Table 3.

Our full sample estimation results for the models with fundamentals in Table 2 show scant significance for the UIP, PPP and MF models. The slope coefficient of the UIP model is significant at the 5% level or higher for one currency (KWD) while it is significant for the PPP model for three currencies (SGD, TRY and TWD). The slope coefficient for the MF model is not significant for any of the currencies. In contrast, the output gap coefficient of the symmetric and asymmetric Taylor rules (TR_s and TR_a) is significant at the 5% level or higher for six currencies and the results appear to suggest that the two Taylor rules might possess predictive power for emerging market currency returns.

The estimation results for the models with technical indicators, presented in Table 3, show sparse significance for the moving average signals over the full sample. However, the coefficients associated with the momentum and, to a lesser extent, relative strength index indicator trading signals are highly significant. The significance of the coefficients of the MOM (9) and MOM (12) signals at the 1% level for almost all of the currencies is particularly striking. Again, we interpret these findings as preliminary evidence that the momentum and, to a lesser extent, relative strength indicators might possess predictive power for our cross-section of emerging market currency returns. We turn next to a more careful assessment of the predictive power of the fundamental and technical indicators using out-of-sample statistical forecast evaluation tests.

6.1.2. Out-of-sample statistical forecast evaluation

The full sample estimation results indicate that the symmetric and asymmetric Taylor rules as well as the momentum and relative strength indicators may possess predictive power for the currency returns of emerging markets. We assess next the out-of-sample predictive performance of the models with fundamentals and technical indicators.

Table 2

Full sample estimation results for models with fundamentals. The table provides the results for the following simple predictive regression: $\Delta s_{it+1} = \alpha + \beta x_{it} + \varepsilon_{it+1}$, for fourteen emerging market currencies. Δs_{t+1} is exchange rate return (defined as the logarithmic change in the spot exchange rate). The first estimated model is the Uncovered Interest Parity (UIP) model which uses the forward premium, defined as the difference between the log of the one-month forward rate and the log of the spot rate, as a predictor: $x_t = f_t - s_t$. The second model is the Purchasing Power Parity (PPP) model, which uses the sixth lag of the real exchange rate as a predictor $x_{it} = p_t - p^*_{it} - s_{it}$ and in which $p_t$and p^*_t are, respectively, the domestic and foreign price levels. The third model is the monetary fundamentals (MF) model which uses the sixth lag of $x_t = (m_t - m^*_{it}) - (y_t - y^*_{it}) - s_t$ and in which $m_t$and m^*_t are the logarithms of the domestic and foreign money supply, respectively, and y_t and y^*_t are the logarithms of the domestic and foreign real output, respectively. The symmetric Taylor rule (TRs), given by: $\Delta s_{it+1} = \alpha + \theta(\pi_{t-6} - \pi^*_{it-6}) + \gamma(y^g_{t-6} - y^{*g}_{it-6}) + \epsilon_{it+1}$, where π_t and π^*_t denote, respectively, the domestic and foreign inflation rates while y^g_t and y^{*g}_t denote, respectively, the domestic and foreign output gaps measured as the percent deviation of real output from its potential. Potential output is estimated using the Hodrick and Prescott (1997) filter. The asymmetric Taylor rule (TRa) given by: $\Delta s_{it+1} = \alpha + \theta(\pi_{t-6} - \pi^*_{t-6}) + \gamma(y^g_{t-6} - y^{*g}_{t-6}) + \delta(p_{t-6} - p^*_{t-6} - s_{t-6}) + u_{it+1}$. The models are estimated over the full sample spanning December 1996 to June 2017. *, ** and *** indicate, respectively, statistical significance at the 10%, 5% and 1% levels, respectively. Statistical inference is conducted using Newey and West (1987) standard errors with automatic bandwidth selection.

	UIP		PPP		MF		TRs			TRa			
	β	R^2	β	R^2	β	R^2	θ	γ	R^2	θ	γ	δ	R^2
CZK	0.575	0.00	0.012	0.00	−0.017	0.00	−0.014	0.105***	0.03	−0.010	0.099***	−0.006	0.04
HKD	−0.048	0.00	0.000	0.00	−0.000	0.00	0.000	−0.005	0.00	0.000	−0.005	−0.000	0.00
HUF	−0.450	0.638	0.010	0.00	−0.007	0.00	0.046	0.148***	0.06	0.048	0.147***	−0.000	0.06
IDR	0.038	0.00	0.052*	0.02	–	–	−0.073	0.051	0.02	−0.062	−0.046	−0.007	0.02
INR	−0.105	0.00	–	–	–	–	–	–	–	–	–	–	–
KWD	2.776***	0.15	–	–	–	–	–	–	–	–	–	–	–
MXN	−0.241	0.00	0.024	0.00	0.000	0.00	−0.014	−0.004	0.00	−0.001	−0.007	−0.025	0.00
PHP	1.481	0.03	0.021*	0.02	−0.004	0.00	−0.015	0.110***	0.04	−0.015	0.109***	−0.000	0.04
SAR	−0.284	0.03	−0.000	0.00	–	–	–	–	–	–	–	–	
SGD	0.234	0.00	0.015**	0.01	−0.010	0.00	−0.017	0.062	0.01	−0.081	0.051	−0.019*	0.02
THB	0.963	0.01	0.040*	0.03	–	–	0.143	0.165**	0.10	0.108	0.149**	−0.012	0.10
TRY	−0.015	0.00	−0.032**	0.03	–	–	0.058***	0.054	0.05	0.079***	0.046	−0.019	0.06
TWD	0.558*	0.00	0.040**	0.04	−0.008	0.00	0.012	0.088***	0.04	0.017	0.062**	−0.028	0.06
ZAR	−2.021	0.01	0.000	0.00	−0.008	0.00	0.014	0.114**	0.03	0.015	0.114**	0.000	0.03

Table 3
Full sample estimation result for models with technical trading signals. The table provides the results from estimating predictive regression: $\Delta s_{it+1} = \alpha + \beta z_{it} + \varepsilon_{it+1}$, where z_{it} is a binary technical trading signal. The predictive regression is estimated for fourteen emerging markets currencies. Δs_{t+1} is the change in the log (spot) exchange rate expressed in USD per unit of the foreign currency. The first technical indicator is the moving average (MA) which identifies an upward (downward) trend if the short moving average $(MA_{s,t})$is greater (less) than the long moving average $(MA_{l,t})$. we compute a simple moving average of the spot exchange rates over the past j months as $MA_t = 1/j\sum_{i=0}^{j-1} S_{t-i}$for each currency pair, for $j = s, l$, where $s(l)$ is the length of the short (long) MA $(s < l)$. The table report the MA results with s = 1, 2, 3 and l = 9,12. The second technical indicator is momentum (MOM), which defines a buy (sell) signal if the price of the spot exchange rate in the current month is greater (less) than or equal to the price m months ago. The table report the MOM results with m = 9,12. The third indicator is the Relative Strength Index (RSI) which identifies overbought and oversold episodes. The two thresholds that we employ to indicate whether a currency is overbought or oversold are 70 and 30, respectively. The models are estimated over the full sample spanning December 1996 to June 2017. *, ** and *** indicate, respectively, statistical significance at the 10%, 5% and 1% levels, respectively. Statistical inference is conducted with Newey and West (1987) standard errors with automatic bandwidth selection.

	MA(1,9)		MA(1,12)		MA(2,9)		MA(1,12)		MA(3,9)		MA(3,12)		MOM(9)		MOM(12)		RSI	
	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2
CZK	0.510	0.01	0.750	0.01	0.697	0.01	0.630	0.01	0.457	0.00	0.470	0.00	1.849^{***}	0.10	1.310^{***}	0.03	1.087^{**}	0.02
HKD	−0.024	0.01	−0.019	0.01	0.032^{***}	0.02	-0.034^{**}	0.02	−0.015	0.00	0.026^{*}	0.01	0.047^{***}	0.10	0.043^{***}	0.03	0.052^{***}	0.05
HUF	0.465	0.00	0.590	0.01	0.454	0.00	0.355	0.00	−0.054	0.00	0.428	0.00	2.007^{***}	0.10	1.685^{***}	0.05	0.871^{*}	0.01
IDR	0.861	0.00	1.056	0.00	0.638	0.00	0.900	0.00	1.129	0.01	1.014	0.00	3.218^{***}	0.10	1.638^{*}	0.01	1.662	0.01
INR	0.446^{*}	0.01	0.445^{*}	0.01	0.459^{*}	0.01	0.448^{*}	0.01	0.487^{*}	0.01	0.306	0.01	1.009^{***}	0.10	0.841^{***}	0.04	0.774^{***}	0.03
KWD	0.125	0.01	0.180^{**}	0.02	0.135	0.01	0.113	0.01	0.129	0.01	0.083	0.00	0.308^{***}	0.10	0.297^{***}	0.04	0.146	0.01
MXN	−0.033	0.00	0.335	0.00	−0.084	0.00	0.091	0.00	−0.148	0.00	−0.233	0.00	1.548^{***}	0.10	1.356^{***}	0.05	1.609^{***}	0.05
PHP	0.616^{**}	0.02	0.701^{**}	0.02	0.591^{*}	0.01	0.664^{**}	0.02	0.676^{**}	0.02	0.618^{**}	0.02	1.401^{***}	0.10	1.026^{***}	0.04	0.696^{*}	0.02
SAR	−0.010	0.00	−0.014	0.01	−0.007	0.00	−0.008	0.00	−0.004	0.00	−0.005	0.00	0.028^{***}	0.00	0.028^{***}	0.03	0.015	0.00
SGD	0.044	0.00	0.007	0.00	−0.072	0.00	0.026	0.00	0.179	0.00	−0.016	0.00	1.026^{***}	0.10	0.680^{***}	0.04	0.575^{**}	0.03
THB	0.599	0.01	0.436	0.00	0.207	0.00	0.281	0.00	0.309	0.00	0.555	0.01	1.381^{***}	0.10	1.161^{***}	0.03	0.649	0.01
TRY	1.043	0.01	0.880	0.01	0.638	0.00	0.881	0.01	0.473	0.00	0.410	0.00	3.270^{***}	0.10	2.826^{***}	0.07	3.462^{***}	0.05
TWD	0.254	0.01	0.112	0.00	0.127	0.00	0.084	0.00	0.093	0.00	0.129	0.00	0.780^{***}	0.10	0.556^{***}	0.03	0.648^{***}	0.04
ZAR	0.930	0.01	1.258^{**}	0.02	0.885	0.01	1.182^{**}	0.02	1.036^{*}	0.01	1.078^{*}	0.01	2.314^{***}	0.10	2.0561^{***}	0.04	2.257^{***}	0.05

As described in Section 4, we estimate the predictive regressions in Eqs. (1)–(7) over the IS period spanning the period December 1996 to August 2008 and generate rolling one-step-ahead forecasts of the returns for our OOS period which extends from September 2008 to June 2017. Tables 4 and 5 provide the OOS statistical forecast evaluation statistics discussed in detail in Section 4. More specifically, Tables 4 and 5 present the R^2_{OOS}, the *MSE-F* statistic of McCracken (2007), the Giacomini and White (2006) test of conditional predictive ability, the Clark and West (2007) test of equal MSEs between a predictive model and the benchmark as well the fluctuations test of Giacomini and Rossi (2010).

A number of interesting observations can be gleaned from the OOS tests. First, our OOS results corroborate the full sample estimation results in that, for the models with fundamentals, the symmetric and asymmetric Taylor rules dominate the other models. In fact, the R^2_{OOS} is positive for the TR_s for CZK, HUF, PHP, TWD and ZAR. The results for the TR_a are slightly weaker in that, relative to the latter currencies, the R^2_{OOS} is not positive for TWD and ZAR. The *MSE-F* test rejects the null of equal predictive ability between the TR_s and the random walk with drift benchmark for CZK, HUF, TWD and ZAR at the 5% level and for

Table 4

Statistical forecast accuracy for out-of-sample forecasts of models with fundamentals. The table provides the Out-of-Sample (OOS) statistical forecast accuracy for the models with fundamentals. The table reports the OOS R^2, the MSE-F test of equal predictive accuracy of McCracken (2007), the Giacomini and White (2006) (GW) test of conditional predictive ability, the Clark and West (2007) (CW) test of equal predictive ability and Giacomini and Rossi (2010) (GR) fluctuations test. Positive *OOS R^2* are in bold. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. A GW statistic succeeded by (+) or (−) indicates, respectively, that the model statistically significantly outperforms or underperforms the random walk benchmark at the 10% level. Giacomini and Rossi (2010) provide critical values at the 5% and 10% levels and the significance of the GR fluctuations test is assessed based on these latter nominal sizes.

	UIP	PPP	MF	TRs	TRa		UIP	PPP	MF	TRs	TRa
			CZK						HKD		
R^2_{OOS}	0.00	−0.01	−0.02	**0.02**	**0.02**	R^2_{OOS}	−0.00	−0.00	−0.01	−0.02	−0.02
MSE-F	0.35	−1.33	−2.64	2.93^{**}	3.08^{**}	MSE-F	−0.13	−0.51	−1.45	−2.14	−2.09
GW	1.78	0.22	0.83	1.08	1.52	GW	0.01	3.09	2.10	3.94	0.56
CW	0.98	0.60	−0.04	1.46^{**}	1.64^{*}	CW	0.64	−0.25	−0.59	−1.23	−0.83
GR	1.09	1.05	1.34	0.69	0.78	GR	0.19	0.01	−0.37	−0.0.27	−0.08
			HUF						IDR		
R^2_{OOS}	−0.00	−0.03	−0.02	**0.03**	**0.02**	R^2_{OOS}	−0.01	−0.01	–	–	–
MSE-F	−0.45	−3.35	−3.06	4.14^{**}	2.78^{**}	MSE-F	−1.13	−1.84	–	–	–
GW	0.43	1.96	1.36	1.68	1.48	GW	$4.97^{(-)}$	0.10	–	–	–
CW	0.51	−0.23	−1.37	1.94^{**}	1.87^{**}	CW	−1.37	0.37	–	–	–
GR	1.35	0.49	0.41	1.14	0.76	GR	−0.80	1.61	–	–	–
			INR						KWD		
R^2_{OOS}	−0.01	–	–	–	–	R^2_{OOS}	−0.08	–	–	–	–
MSE-F	−1.25	–	–	–	–	MSE-F	−7.99	–	–	–	–
GW	0.88	–	–	–	–	GW	1.46	–	–	–	–
CW	−0.76	–	–	–	–	CW	−0.72	–	–	–	–
GR	0.11	–	–	–	–	GR	1.07	–	–	–	–
			MXN						PHP		
R^2_{OOS}	−0.00	−0.02	−0.02	−0.02	−0.02	R^2_{OOS}	−0.02	−0.03	0.00	**0.04**	**0.03**
MSE-F	−0.83	−2.22	−2.80	−2.20	−2.99	MSE-F	−2.97	−3.93	0.21	4.92^{***}	3.52^{**}
GW	$5.08^{(-)}$	0.68	3.59	1.91	1.42	GW	1.21	1.38	0.32	2.93	4.00
CW	−1.99	−0.02	−0.00	−1.07	−0.33	CW	−0.57	0.15	0.72	1.88^{**}	1.64^{**}
GR	−1.29	0.62	1.64	0.36	0.46	GR	0.61	2.07^{*}	1.72	1.61	1.91
			SAR						SGD		
R^2_{OOS}	−0.31	−0.00	–	–	–	R^2_{OOS}	0.00	−0.01	−0.03	−0.02	−0.03
MSE-F	−25.55	−0.93	–	–	–	MSE-F	0.55	−1.63	−3.89	−2.18	−3.85
GW	$5.20^{(-)}$	1.68	–	–	–	GW	1.54	0.56	1.07	1.31	1.62
CW	−1.17	−1.14	–	–	–	CW	0.73	−0.06	−0.92	0.21	−0.15
GR	0.61	0.87	–	–	–	GR	1.25	1.71	0.38	0.21	0.72
			THB						TRY		
R^2_{OOS}	−0.03	−0.07	–	−0.05	−0.05	R^2_{OOS}	0.00	**0.02**	–	−0.07	−0.08
MSE-F	−3.52	−7.29	–	−5.58	−5.66	MSE-F	2.33^{**}	−7.15	–	−7.20	−7.90
GW	$6.60^{(-)}$	1.49	–	1.55	1.40	GW	$8.22^{(+)}$	1.40	–	0.99	1.01
CW	−1.89	0.19	–	0.51	0.71	CW	3.07^{***}	−0.54	–	0.42	0.08
GR	−0.90	1.85	–	0.86	1.48	GR	2.66^{**}	1.56	–	0.74	0.39
			TWD						ZAR		
R^2_{OOS}	0.00	−0.00	−0.01	**0.03**	−0.24	R^2_{OOS}	**0.01**	−0.02	−0.00	**0.03**	−0.00
MSE-F	0.57	−0.23	−1.16	3.85^{**}	−20.81	MSE-F	1.18^{*}	−2.60	−0.37	3.53^{**}	−0.58
GW	2.18	0.61	$4.65^{(-)}$	0.64	3.68	GW	$6.40^{(+)}$	0.47	2.20	0.86	1.23
CW	0.72	0.87	−0.20	1.84^{**}	0.61	CW	1.17	−0.17	−0.27	1.63^{*}	0.96
GR	2.42^{***}	1.06	1.17	0.83	−0.85	GR	2.53^{***}	0.73	2.07^{*}	0.86	1.31

Table 5
Statistical forecast accuracy for out-of-sample forecasts for models with technical indicators. The table provides the Out-of-Sample (OOS) statistical forecast accuracy for the models with technical indicators. The table reports the OOS R^2, the MSE-F test of McCracken (2007), the Giacomini and White (2006) (GW) test, the Clark and West (2007) (CW) test and the Giacomini and Rossi (2010) (GR) test. Positive OOS R^2 are in bold. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. A GW statistic succeeded by (+) or (−) indicates, respectively, that the model statistically significantly outperforms or underperforms the random walk benchmark at the 10% level.

	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)	RSI
					CZK				
R^2_{OOS}	−0.02	−0.01	−0.01	−0.01	−0.02	−0.02	**0.04**	**0.01**	−0.04
MSE-F	−2.12	−1.26	−1.52	−1.60	−2.85	−2.89	5.41***	1.67*	−4.30
GW	1.49	1.54	2.10	2.15	3.75	3.77	1.10	1.76	2.90
CW	−1.04	−0.12	−0.14	−0.27	−1.06	−1.19	2.07**	1.16	−1.17
GR	0.20	0.54	0.82	0.78	0.07	0.59	1.73	2.32*	1.61
					HKD				
R^2_{OOS}	**0.01**	**0.01**	**0.02**	**0.01**	0.00	**0.01**	**0.05**	**0.01**	**0.13**
MSE-F	1.92**	1.10*	2.22**	1.12*	0.56	1.45	5.92***	1.71*	16.96***
GW	2.61	0.26	1.94	0.14	1.02	1.17	1.53	0.34	9.37$^{(+)}$
CW	1.69*	1.27	1.80**	1.43*	0.93	1.47*	2.43**	1.47*	4.06**
GR	1.67	2.53***	1.30	1.87	1.26	1.22	1.64	0.40	2.69**
					HUF				
R^2_{OOS}	−0.02	−0.02	−0.02	−0.02	−0.04	−0.03	**0.02**	0.00	−0.00
MSE-F	−2.23	−2.22	−2.83	−2.64	−4.59	−3.22	3.08**	0.52	−0.34
GW	2.26	3.00	3.81	2.90	4.93$^{(-)}$	4.76$^{(-)}$	2.00	0.54	0.10
CW	−1.10	−0.97	−1.87	−1.58	−1.60	−2.15	1.74**	0.99	0.64
GR	−1.20	−1.35	−0.92	−0.08	0.25	−1.01	2.65**	2.08*	1.87
					IDR				
R^2_{OOS}	−0.03	−0.01	−0.05	−0.02	−0.02	−0.06	0.00	0.00	−0.00
MSE-F	−3.15	−1.52	−5.11	−2.68	−2.50	−6.34	0.45	0.36	−0.47
GW	1.90	0.60	3.04	1.91	0.64	2.31	0.01	0.18	0.03
CW	−0.88	−0.08	−1.61	−0.61	−0.63	−1.33	1.30*	0.99	1.08
GR	1.61	1.79	0.38	1.33	1.13	0.72	1.15	0.09	0.81
					INR				
R^2_{OOS}	−0.06	−0.07	−0.04	−0.05	−0.04	−0.05	−0.01	−0.02	−0.00
MSE-F	−6.22	−6.93	−4.93	−5.32	−4.46	−5.76	−1.53	−2.42	−0.68
GW	2.99	3.20	1.28	1.25	0.90	1.56	0.38	0.29	1.41
CW	−0.63	−0.70	0.01	0.00	0.19	−0.19	1.10	0.76	0.98
GR	−1.09	−1.17	−0.48	−0.59	−0.15	−0.93	1.48	2.17*	1.44
					KWD				
R^2_{OOS}	−0.07	−0.07	−0.07	−0.10	−0.07	−0.11	−0.06	−0.09	−0.09
MSE-F	−7.43	−7.60	−7.67	−9.99	−7.71	−10.76	−6.11	−8.78	−8.82
GW	3.35	1.13	1.03	2.20	1.06	1.78	0.67	1.31	1.70
CW	−0.16	0.52	−0.15	−0.33	−0.13	−0.54	0.96	0.70	−0.37
GR	1.47	1.69	1.84	1.26	1.52	1.31	1.52	1.39	1.04
					MXN				
R^2_{OOS}	−0.04	−0.03	−0.05	−0.04	−0.06	−0.05	**0.04**	0.00	**0.02**
MSE-F	−4.51	−3.44	−5.38	−4.17	−6.29	−5.90	4.87***	0.60	2.31**
GW	4.58	0.89	2.24	2.20	5.01$^{(-)}$	2.04	1.68	1.40	0.30
CW	−1.24	−0.79	−1.40	−1.07	−1.38	−1.16	1.97**	1.08	1.51*
GR	−0.27	1.31	0.02	0.93	−0.78	0.43	1.52	1.39	1.04
					PHP				
R^2_{OOS}	−0.04	−0.03	−0.02	−0.02	−0.02	−0.02	**0.08**	**0.05**	−0.03
MSE-F	−4.14	−3.69	−2.50	−2.21	−2.38	−2.56	10.40***	5.83***	−3.33
GW	1.06	1.09	2.52	2.30	2.80	2.62	2.13	2.12	1.53
CW	−0.22	0.24	0.11	0.34	0.22	0.13	3.11***	2.43***	−0.08
GR	−0.27	1.31	0.02	0.93	−0.78	0.43	1.52	1.39	1.04
					SAR				
R^2_{OOS}	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.02	−0.02	−0.07
MSE-F	−0.58	−0.59	−0.70	−0.61	−0.55	−0.38	−2.62	−3.06	−6.97
GW	2.09	1.80	3.11	2.02	2.66	2.17	1.48	1.45	1.50
CW	0.35	0.62	0.15	0.11	−0.74	−0.20	1.59*	1.49*	2.04**
GR	1.11	0.64	1.16	0.79	1.51	1.19	0.33	0.41	0.71

(continued on next page)

Table 5 (*continued*)

	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)	RSI
					SGD				
R^2_{OOS}	−0.04	−0.03	−0.05	−0.04	−0.03	−0.03	**0.04**	**0.02**	−0.00
MSE-F	−4.36	−3.94	−5.44	−4.90	−3.59	−3.78	5.17^{***}	3.14^{**}	−0.75
GW	3.47	3.63	2.51	2.61	2.00	2.18	0.94	1.80	0.37
CW	−1.71	−1.50	−1.50	−1.42	−1.20	−1.31	2.23^{**}	1.74^{**}	0.22
GR	−0.67	−0.41	−0.13	−0.36	−0.22	−0.39	3.48^{**}	2.24^{*}	1.66
					THB				
R^2_{OOS}	−0.03	−0.03	−0.05	−0.03	−0.04	−0.03	**0.05**	**0.06**	−0.02
MSE-F	−3.94	−3.66	−5.44	−3.90	−4.23	−3.71	5.65^{***}	6.93^{***}	−2.20
GW	1.71	3.21	$4.88^{(-)}$	3.18	3.19	1.47	1.67	1.33	1.09
CW	−1.71	−1.50	−1.50	−1.42	−1.20	−1.31	2.20^{**}	2.34^{***}	−0.17
GR	−0.67	−0.41	−0.13	−0.36	−0.22	−0.39	3.29^{***}	2.61^{**}	0.60
					TRY				
R^2_{OOS}	−0.07	−0.06	−0.11	−0.12	−0.06	−0.08	**0.01**	−0.00	−0.00
MSE-F	−7.09	−6.72	−11.34	−11.77	−6.83	−8.03	2.06^{**}	−0.58	−0.62
GW	1.13	1.36	1.62	1.54	1.41	1.89	1.63	0.01	0.31
CW	−0.67	−0.50	−0.77	−0.95	−0.14	−0.36	2.47^{***}	1.47^{*}	0.87
GR	0.68	0.49	−0.00	−0.64	−0.56	−0.64	1.77	1.89	1.70
					TWD				
R^2_{OOS}	−0.01	−0.02	−0.01	−0.05	−0.02	−5.39	**0.03**	**0.01**	**0.03**
MSE-F	−1.33	−2.10	−1.73	−5.82	−2.18	−0.08	4.24^{***}	1.25^{*}	3.45^{**}
GW	0.55	2.55	1.57	3.62	1.67	3.77	1.23	0.42	0.96
CW	−0.26	−0.97	−0.76	−1.40	−0.93	−1.48	1.84^{**}	1.02	2.03^{**}
GR	−0.59	−0.28	−0.29	0.25	0.15	0.06	2.40^{**}	1.89	2.16^{*}
					ZAR				
R^2_{OOS}	0.00	**0.02**	−0.00	−0.00	−0.00	0.00	**0.03**	**0.03**	**0.02**
MSE-F	0.62	2.62^{**}	−0.07	−0.32	−0.40	0.07	3.65^{**}	3.86^{**}	3.03^{**}
GW	1.37	$4.79^{(+)}$	3.78	0.36	0.59	0.19	3.82	$5.12^{(+)}$	$6.37^{(+)}$
CW	0.89	1.88^{**}	0.54	0.56	0.34	0.59	2.22^{**}	2.19^{**}	2.13^{**}
GR	1.53	3.55^{***}	0.87	1.89	0.52	0.83	3.08^{**}	3.09^{**}	2.26^{*}

PHP at the 1% level. Again, our results are slightly weaker for the TR_a. The Clark and West (2007) statistic rejects the null of equal predictive ability between the TR_s and the random walk with drift benchmark for CZK, HUF, TWD and PHP at the 5% level and for ZAR at the 10% level. The results of the TR_a are weaker than those of the TR_s in that the CW test does not reject the null of equal predictive ability between the TR_a and the random walk for TWD and ZAR. In terms of OOS forecasting power, however, both variants of the Taylor rule appear to perform significantly better than the UIP, PPP and MF models.

Second, the OOS results for the technical indicators are also in line with the full sample estimation results. More specifically, the momentum and relative strength index indicators outperform the random walk benchmark for a substantial number of the emerging market currencies. Conversely, the OOS forecasts generated from the moving average signals do not outperform, according to the R^2_{OOS}, the random walk for any of the currencies except HKD and ZAR (for the MA (1,12)). The R^2_{OOS} is positive for the MOM (9) indicator for CZK, HKD, HUF, MXN, PHP, SGD, THB, TRY, TWD and ZAR. The R^2_{OOS} is positive for a lesser number of currencies when the MOM (12) indicator is used. Nonetheless, the results continue to suggest that the momentum indicator outperforms the random walk for a sizeable number of currencies. The $R^2_{OOS}$for the relative strength indicator is positive for HKD, MXN, TWD and ZAR. Using the *MSE-F* test, the null of equal predictive accuracy is rejected for MOM (9) forecasts at the 1% level for CZK, HKD, MXN, PHP, SGD, THB and TWD while it is rejected at the 5% level for HUF, TRY and ZAR. Using the Clark and West (2007) statistic, we reject the null of equal OOS predictive accuracy between the MOM (9) and random walk forecasts at the 5% level for CZK, HKD, HUF, SGD, THB, TWD and ZAR and at the 1% level for PHP and TRY. We fail to reject the null of equal conditional predictive accuracy for any of the currencies as evinced by the insignificant Giacomini and White (2006) statistic. It is worthwhile to note that the OOS forecasts obtained from our best-performing model with technical indicators, namely MOM (9), also exhibit stability. In fact, the Giacomini and Rossi (2010) fluctuations test shows that the MOM (9) forecasts outperform the random walk benchmark at the 5% level for HUF, SGD, TWD, and ZAR and at the 1% level for THB.

Interestingly, our results also suggest that our OOS forecasts using the MOM (9) forecasts appear to outperform those from symmetric Taylor rule. The latter conclusion can be garnered from the larger number of currencies, vis-à-vis the symmetric Taylor rule forecasts, for which the momentum forecasts outperform the random walk. The profitability of MOM (9) is not surprising in light of the evidence in Moskowitz et al. (2012) which suggests that time series momentum is pervasive across asset classes. We turn next to assessing the economic significance of our OOS forecast.

Table 6
Economic evaluation of exchange rate predictability for models with fundamentals. The table provides profitability of trading based on the sign of the predicted returns from one of the models with fundamentals. The models with fundamentals that we consider are Uncovered Interest Parity (UIP), Purchasing Power Parity (PPP), Monetary Fundamentals (MF), Symmetric Taylor Rule (TRs) and asymmetric Taylor rule (TRa). We consider a simple trading strategy according to which the investor goes long (short) if the predicted return from the model is positive (negative) and assume that the investor transacts in the spot market. The table reports the annualized average net-of-transaction costs realized returns, standard deviation, skewness, excess kurtosis, Sharpe and Sortino ratios. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	UIP	PPP	MF	TRs	TRa		UIP	PPP	MF	TRs	TRa
			CZK						HKD		
Average Return	−3.45	−6.83	−0.29	7.33*	4.83	Average Return	−0.10	−0.10	−0.09	−0.27**	−0.25*
Std. Dev.	13.19	13.08	13.23	13.05	13.15	Std. Dev.	0.40	0.40	0.40	0.40	0.40
Skewness	−0.46	0.08	−0.56	0.12	0.23	Skewness	−1.01	−1.18	−1.09	−1.02	−1.03
Excess Kurtosis	0.88	1.12	1.00	0.99	0.93	Excess Kurtosis	4.29	4.24	4.29	4.08	4.09
Sharpe Ratio	−0.26	−0.52	−0.02	0.56	0.36	Sharpe Ratio	−0.26	−0.26	−0.24	−0.69	−0.64
Sortino Ratio	−0.34	−0.77	−0.02	0.88	0.60	Sortino Ratio	−0.28	−0.28	−0.26	−0.78	−0.72
			HUF						IDR		
Average Return	−2.13	−3.30	−5.14	14.80***	13.81**	Average Return	−0.84	4.05	–	–	–
Std. Dev.	16.74	16.72	16.68	16.19	16.26	Std. Dev.	10.64	10.5	–	–	–
Skewness	−0.70	−0.40	−1.16	0.79	0.81	Skewness	0.59	0.62	–	–	–
Excess Kurtosis	3.43	3.46	3.15	3.18	3.14	Excess Kurtosis	5.88	5.68	–	–	–
Sharpe Ratio	−0.12	−0.19	−0.30	0.91	0.84	Sharpe Ratio	−0.07	0.38	–	–	–
Sortino Ratio	−0.15	−0.25	−0.35	1.57	1.49	Sortino Ratio	−0.10	0.54	–	–	–
			INR						KWD		
Average Return	0.96	–	–	–	–	Average Return	1.99	–	–	–	–
Std. Dev.	9.40	–	–	–	–	Std. Dev.	3.18	–	–	–	–
Skewness	0.10	–	–	–	–	Skewness	0.30	–	–	–	–
Excess Kurtosis	1.12	–	–	–	–	Excess Kurtosis	11.15	–	–	–	–
Sharpe Ratio	0.10	–	–	–	–	Sharpe Ratio	0.62	–	–	–	–
Sortino Ratio	0.15	–	–	–	–	Sortino Ratio	0.77				
			MXN						PHP		
Average Return	6.39	2.42	−1.21	0.33	5.68	Average Return	−2.75	−1.44	−0.95	2.41	1.55
Std. Dev.	12.44	12.56	12.57	12.58	12.47	Std. Dev.	5.66	5.70	5.71	5.67	5.70
Skewness	0.81	0.37	−0.76	−0.04	0.748	Skewness	0.28	0.22	−0.19	−0.00	0.01
ExcessKurtosis	2.03	2.35	2.34	2.43	2.10	Excess Kurtosis	0.09	−0.00	−0.11	−0.07	−0.07
Sharpe Ratio	0.51	0.19	−0.09	0.02	0.45	Sharpe Ratio	−0.48	−0.25	−0.16	0.42	0.27
Sortino Ratio	0.97	0.29	−0.11	0.03	0.80	Sortino Ratio	−0.77	−0.40	−0.24	0.68	0.43
			SAR						SGD		
Average Return	−0.13**	−0.11**	–	–	–	Average Return	0.33	−1.92	0.30	1.09	−1.02
Std. Dev.	0.17	0.17	–	–	–	Std. Dev.	6.73	6.71	6.73	6.72	6.72
Skewness	−4.24	−3.05	–	–	–	Skewness	−0.67	−0.67	−0.54	0.51	−0.65
Excess Kurtosis	18.81	19.72	–	–	–	Excess Kurtosis	2.28	2.041	2.27	2.15	2.13
Sharpe Ratio	−0.73	−0.62	–	–	–	Sharpe Ratio	0.04	−0.28	0.04	0.16	−0.15
Sortino Ratio	−0.58	−0.52	–	–	–	Sortino Ratio	0.06	−0.35	0.06	0.26	−0.19
			THB						TRY		
Average Return	−0.34	−0.77	–	−0.61	2.53	Average Return	12.35***	2.13	–	4.67	2.48
Std. Dev.	5.57	5.56	–	5.57	5.52	Std. Dev.	12.83	13.31	–	13.25	13.30
Skewness	−0.17	0.06	–	−0.20	0.09	Skewness	1.09	−0.92	–	−1.08	−1.02
Excess Kurtosis	−0.08	−0.05	–	−0.09	−0.12	Excess Kurtosis	3.80	4.54	–	4.90	4.60
Sharpe Ratio	−0.06	−0.13	–	−0.11	0.45	Sharpe Ratio	0.96	0.160	–	0.35	0.18
Sortino Ratio	−0.09	−0.22	–	−0.17	0.81	Sortino Ratio	2.15	0.21	–	0.44	0.23
			TWD						ZAR		
Average Return	−0.21	0.78	−1.74	1.37	0.16	Average Return	3.63	−1.06	−1.47	6.42	0.19
Std. Dev.	5.28	5.27	5.26	5.26	5.28	Std. Dev.	16.34	16.37	16.37	16.27	16.37
Skewness	−0.01	0.39	0.09	0.56	0.43	Skewness	0.59	−0.61	−0.46	0.43	−0.30
Excess Kurtosis	0.84	0.78	0.90	0.68	0.83	Excess Kurtosis	1.50	1.60	1.60	1.49	1.65
Sharpe Ratio	−0.03	0.14	−0.33	0.26	0.03	Sharpe Ratio	0.22	−0.06	−0.08	0.39	0.01
Sortino Ratio	−0.06	0.26	−0.50	0.49	0.05	Sortino Ratio	0.39	−0.08	−0.12	0.67	0.01

6.2. Economic evaluation

We next assess the profitability of trading based on the predicted OOS return from one of the competing models. In specific, our trading strategy is based on the sign of the predicted return and we consider three measures of profitability: the net-of-transaction cost realized return, the Sharpe and Sortino ratios. The latter two ratios are measures of risk-adjusted returns

Table 7
Economic evaluation of exchange rate predictability for models with technical indicators. The table provides profitability of trading based on the sign of the predicted returns from one of the models with technical indicators. The technical indicators that we consider are: moving averages with different window lengths (MA (1,9), MA(1,12), MA(2,9), MA(2,12), MA(3,9) and MA(3,12)), momentum indicators (MOM (9) and MOM (12)) as well as the Relative Strength Index (RSI). We consider a simple trading strategy according to which the investor goes long (short) if the predicted return from the model is positive (negative) and assume that the investor transacts in the spot market. The table reports the annualized average net-of-transaction costs realized returns, standard deviation, skewness, excess kurtosis, Sharpe and Sortino ratios.

	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)	RSI
					CZK				
Average return	−6.19	−2.06	−3.37	−7.06*	−7.45*	−4.41	9.31**	5.36	−4.99
Std. Dev.	13.11	13.22	13.20	13.07	13.05	13.17	12.95	13.14	13.15
Skewness	−0.65	−0.06	−0.09	−0.03	−0.01	−0.14	0.11	0.40	−0.76
Excess Kurtosis	0.69	1.01	1.01	1.05	1.07	0.99	1.02	0.86	0.70
Sharpe Ratio	−0.47	−0.16	−0.26	−0.54	−0.57	−0.34	0.72	0.41	−0.38
Sortino Ratio	−0.60	−0.23	−0.36	−0.77	−0.82	−0.47	1.16	0.73	−0.47
					HKD				
Average return	0.24*	0.00	0.27*	0.23*	0.02	0.27*	0.35***	0.21*	0.50***
Std. Dev.	0.40	0.41	0.40	0.40	0.41	0.40	0.40	0.40	0.38
Skewness	0.91	−0.63	1.08	0.87	−0.20	1.11	1.08	1.03	−0.46
Excess Kurtosis	4.19	4.57	4.05	4.22	4.58	4.02	4.04	4.13	6.76
Sharpe Ratio	0.59	0.00	0.67	0.57	0.06	0.67	0.89	0.53	1.32
Sortino Ratio	0.90	0.00	1.11	0.86	0.08	1.14	1.55	0.88	1.55
					HUF				
Average return	−8.17	−4.23	−5.68	−12.96**	−10.65	−7.09	11.61**	8.22*	6.58
Std. Dev.	16.58	16.71	16.67	16.33	16.47	16.63	16.41	16.58	16.64
Skewness	−0.03	0.51	−0.10	0.14	−0.98	0.12	0.92	1.04	0.42
Excess Kurtosis	3.66	3.73	3.56	4.05	3.03	3.70	3.06	3.06	3.43
Sharpe Ratio	−0.49	−0.25	−0.34	−0.79	−0.65	−0.43	0.71	0.50	0.40
Sortino Ratio	−0.64	−0.37	−0.44	−1.06	−0.76	−0.58	1.26	0.95	0.60
					IDR				
Average return	0.30	2.30	0.36	1.82	0.93	−1.21	8.11**	6.99*	8.02**
Std. Dev.	10.64	10.62	10.64	10.63	10.64	10.64	10.38	10.45	10.39
Skewness	0.84	0.69	0.85	0.72	0.77	−0.98	0.43	0.44	0.44
Excess Kurtosis	5.79	5.69	5.79	5.70	5.75	5.70	6.03	5.92	6.01
Sharpe Ratio	0.03	0.22	0.03	0.17	0.09	−0.11	0.78	0.67	0.77
Sortino Ratio	0.04	0.31	0.05	0.25	0.13	−0.14	0.98	0.84	1.00
					INR				
Average return	0.33	0.80	1.82	1.81	2.93	1.35	8.42***	6.23**	7.61**
Std. Dev.	9.41	9.40	9.39	9.39	9.37	9.40	9.08	9.23	9.14
Skewness	0.35	0.31	0.26	0.24	0.26	0.07	0.13	0.08	0.12
Excess Kurtosis	1.12	1.10	1.08	1.08	1.05	1.12	1.16	1.15	1.15
Sharpe Ratio	0.04	0.09	0.19	0.19	0.31	0.14	0.93	0.68	0.83
Sortino Ratio	0.06	0.13	0.30	0.30	0.50	0.21	1.44	1.01	1.29
					KWD				
Average return	−0.11	1.18	0.32	−0.06	0.15	−0.79	2.14**	1.61*	−0.32
Std. Dev.	3.24	3.22	3.24	3.24	3.24	3.23	3.18	3.21	3.24
Skewness	−0.28	1.46	−0.38	−0.26	−0.35	−0.19	1.35	1.41	−0.28
Excess Kurtosis	10.66	10.27	10.73	10.66	10.69	10.72	10.41	10.27	10.65
Sharpe Ratio	−0.03	0.37	0.10	−0.02	0.04	−0.25	0.67	0.50	−0.10
Sortino Ratio	−0.04	0.57	0.11	−0.02	0.05	−0.29	1.00	0.78	−0.11
					MXN				
Average return	5.70	3.80	2.73	6.39	0.47	4.46	13.11***	9.67**	11.82***
Std. Dev.	12.47	12.53	12.56	12.44	12.58	12.52	11.99	12.27	12.11
Skewness	0.84	0.90	−0.16	0.81	0.48	0.67	0.51	0.54	0.62
Excess Kurtosis	2.05	2.14	2.49	2.04	2.41	2.20	2.28	2.18	2.12
Sharpe Ratio	0.46	0.30	0.22	0.51	0.04	0.36	1.09	0.79	0.98
Sortino Ratio	0.88	0.59	0.31	0.98	0.06	0.63	1.72	1.26	1.68
					PHP				
Average return	−1.14	−0.23	0.51	1.29	1.22	1.33	6.17***	4.74***	1.05
Std. Dev.	5.71	5.72	5.72	5.71	5.71	5.71	5.43	5.55	5.71
Skewness	0.01	−0.30	−0.02	−0.30	−0.30	−0.31	−0.26	−0.26	−0.13
Excess Kurtosis	−0.07	−0.08	−0.07	0.01	0.01	0.01	0.28	0.19	−0.04
Sharpe Ratio	−0.20	−0.04	0.09	0.23	0.21	0.23	1.14	0.85	0.18
Sortino Ratio	−0.30	−0.06	0.14	0.32	0.30	0.33	1.69	1.26	0.27

Table 7 (*continued*)

	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)	RSI
					SAR				
Average return	0.04	0.05	0.03	0.03	−0.10	−0.09	0.10*	0.10*	0.09*
Std. Dev.	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Skewness	0.18	0.19	0.23	0.27	−4.23	−4.19	1.80	1.83	1.82
Excess Kurtosis	20.76	20.84	20.69	20.69	18.90	19.04	20.56	20.51	20.45
Sharpe Ratio	0.22	0.27	0.16	0.17	−0.56	−0.48	0.58	0.56	0.52
Sortino Ratio	0.21	0.27	0.16	0.18	−0.42	−0.36	0.71	0.72	0.66
					SGD				
Average return	−1.48	−2.99	−1.48	−1.48	−0.87	−2.34	5.50**	3.25*	0.42
Std. Dev.	6.72	6.68	6.72	6.72	6.73	6.70	6.54	6.67	6.73
Skewness	−0.58	−0.57	−0.58	−0.58	−0.65	−0.58	0.32	−0.60	−0.57
Excess Kurtosis	2.11	2.01	2.11	2.11	2.15	2.05	2.19	2.68	2.29
Sharpe Ratio	−0.22	−0.45	−0.22	−0.22	−0.13	−0.35	0.84	0.49	0.06
Sortino Ratio	−0.29	−0.59	−0.29	−0.29	−0.17	−0.46	1.30	0.64	0.08
					THB				
Average return	−1.01	−0.32	−1.99	−1.52	−0.70	0.20	5.56***	4.85***	−0.33
Std. Dev.	5.57	5.57	5.54	5.56	5.57	5.57	5.34	5.39	5.57
Skewness	0.11	0.15	0.04	0.10	−0.02	0.11	0.06	0.12	−0.06
Excess Kurtosis	−0.05	−0.06	−0.05	−0.04	−0.07	−0.07	−0.16	−0.21	−0.07
Sharpe Ratio	−0.18	−0.06	−0.36	−0.27	−0.13	0.04	1.04	0.90	−0.06
Sortino Ratio	−0.30	−0.10	−0.58	−0.45	−0.20	0.06	1.90	1.66	−0.09
					TRY				
Average return	1.94	3.73	4.07	4.00	7.81	7.35	14.68***	13.02***	13.74***
Std. Dev.	13.31	13.28	13.27	13.27	13.13	13.15	12.63	12.78	12.71
Skewness	−0.86	−0.95	−0.95	−0.90	1.08	1.12	1.04	1.06	1.09
Excess Kurtosis	4.52	4.73	4.77	4.74	3.85	3.84	3.96	3.86	3.85
Sharpe Ratio	0.15	0.28	0.31	0.30	0.60	0.56	1.16	1.02	1.08
Sortino Ratio	0.19	0.37	0.40	0.40	1.24	1.19	2.54	2.22	2.46
					TWD				
Average return	−1.39	−0.33	−0.79	−0.58	−1.69	0.02	4.16**	2.60	3.58**
Std. Dev.	5.27	5.28	5.28	5.28	5.26	5.28	5.14	5.23	5.18
Skewness	0.05	−0.04	0.05	−0.05	0.12	−0.15	0.29	−0.17	−0.17
Excess Kurtosis	0.88	0.85	0.86	0.84	0.91	0.85	0.67	0.99	1.05
Sharpe Ratio	−0.26	−0.06	−0.15	−0.11	−0.32	0.00	0.81	0.50	0.69
Sortino Ratio	−0.40	−0.09	−0.23	−0.16	−0.49	0.00	1.42	0.74	1.01
					ZAR				
Average return	6.20	9.85**	5.11	4.93	4.67	6.25	12.23***	11.99***	11.20**
Std. Dev.	16.28	16.13	16.31	16.32	16.32	16.28	15.99	16.00	16.05
Skewness	0.63	0.51	0.48	0.23	0.51	0.18	0.45	0.46	0.47
Excess Kurtosis	1.41	1.38	1.50	1.59	1.50	1.61	1.41	1.40	1.39
Sharpe Ratio	0.38	0.61	0.31	0.30	0.29	0.38	0.77	0.75	0.70
Sortino Ratio	0.71	1.11	0.54	0.48	0.50	0.61	1.35	1.33	1.24

given that they account for risk as measured by the standard deviation. The Sharpe ratio is the ratio of net annualized return to annualized volatility while the Sortino ratio is the ratio of annualized net return to annualized 'bad' volatility which corresponds to the negative returns only. A large Sortino ratio thus implies a low risk of large losses. In order to obtain annualized figures, we multiply the monthly average net returns by 12 and the monthly standard deviation by $\sqrt{12}$.

Our measures of profitability are reported in Tables 6 and 7 for the predictive regressions using fundamentals and technical indicators, respectively. We also report skewness and kurtosis since both Sharpe and Sortino ratios do not account for higher moments of the return distributions. Consider first the results from the trading strategies based on the sign of the predicted returns from the models with fundamentals. The results show that the returns from trading based on the predicted sign of the UIP, PPP and MF models are predominantly negative. In fact, the average net-of-transaction costs realized returns are negative for eight of the currencies when the UIP and PPP models are employed and for seven of the currencies when the MF model is used. In contrast, the average net returns are positive for eight currencies when the currency return forecast is generated from the TR_s and TR_a but significantly so only for two currencies, at the 10% level or higher, for the TR_s. Overall, we view the profitability results as broadly consistent with our findings from the statistical forecast accuracy tests. In line with our findings for the average net-of-transaction cost returns, the Sharpe and Sortino ratios from trading based on the TR_s are larger than those of the competing models for CZK, HUF, PHP, SGD, TWD and ZAR. It is interesting to note that, for the latter currencies, the excess kurtosis of the net realized returns of the TR_s is comparable to (or lower than) that of the competing models and that the realized return distribution is positively skewed.

Table 8
Economic evaluation of exchange rate predictability for equally weighted portfolios. The table provides the profitability results from forming a portfolio based on the sign of the predicted exchange rate returns from one of the competing models. We assess the profitability of trading a basket of currencies based on the sign of the predicted return from the competing models by forming portfolios. At the portfolio level, the net-of-transaction cost realized return on a portfolio formed based on the sign of the predicted return from model j is an equally weighted average of the net realized return. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. All the returns and standard deviations are annualized and in percent.

	Average return	Std. Dev.	Skewness	Excess Kurtosis	Sharpe Ratio	Sortino Ratio
	Models with Fundamentals					
UIP	1.12	3.19	0.25	2.67	0.35	0.51
PPP	−0.44	2.93	−0.74	1.45	−0.15	−0.19
MF	−0.76	3.55	−1.66	7.05	−0.21	−0.23
TRs	2.68	3.39	0.96	5.19	0.79	1.24
TRa	2.14	3.40	0.37	2.25	0.63	0.94
	Models with Technical Indicators					
MA(1,9)	−0.34	3.42	−0.30	1.40	−0.10	−0.13
MA(1,12)	0.82	4.01	0.44	3.11	0.21	0.30
MA(2,9)	0.14	3.84	0.17	1.84	0.04	0.05
MA(2,12)	−0.22	3.76	−0.10	2.21	−0.06	−0.08
MA(3,9)	−0.23	3.65	−0.44	1.46	−0.06	−0.08
MA(3,12)	0.38	3.97	−0.05	2.58	0.10	0.13
MOM(9)	7.25***	5.34	0.84	4.53	1.36	2.18
MOM(12)	5.63***	5.18	1.14	5.46	1.09	1.88
RSI	4.21***	3.68	0.02	1.52	1.14	1.69
	Benchmark Portfolios					
Carry	6.60*	10.76	1.22	5.24	0.61	1.24
Momentum	0.63	11.24	0.98	4.98	0.06	0.10
1/N	−3.18	6.74	−0.89	2.11	−0.47	−0.47

The profitability results suggest that trading based on the sign the MOM (9) and, to a lesser extent, MOM (12) and RSI indicators generates positive and highly significant net-of-transaction cost returns for the majority of the currencies. These results corroborate the statistical forecast accuracy results which document the high predictive accuracy of these indicators. Namely, trading based on the sign of the predicted MOM (9) returns generates positive and statistically significant net-of-transaction costs returns for CZK, HUF, IDR, KWD, SGD and TWD at the 5% level, HKD, INR, MXN, PHP, THB, TRY and ZAR at the 1% as well as SAR at the 10% level. That is, the net-of-transaction cost returns are positive and significant for thirteen out of fourteen currencies at the 5% level or higher. The sizeable number of currencies for which trading on the sign of the MOM (9) forecast yields positive net-of-transaction costs returns is indicative of the MOM (9) indicator's success in predicting the sign of the actual return.

The results for the MOM (12) and RSI are, albeit to a lesser degree, also favorable. In fact, the net returns from trading based on the sign of the MOM (12) forecast are positive and significant at the 10% level for HKD, HUF, IDR, KWD, SAR and SGD, at the 5% level for INR and MXN as well as the 1% level for PHP, THB, TRY and ZAR. The net-of-transaction costs realized returns for the RSI are positive and significant at the 5% level or higher for HKD, IDR, INR, MXN, TRY, TWD and ZAR. Again, the Sharpe ratios of the MOM(9) net returns (Sortino and Sharpe ratio) are positive and generally larger than of any of the competing models for all the currencies (except for HKD). The second and third largest Sharpe and Sortino ratios alternate between the MOM (12) and RSI net returns. In addition, except for PHP, the excess kurtosis of the realized returns of the MOM (9) is comparable to (or lower than) that of competing models while the return distribution is, with the exception of PHP, positively skewed. Overall, our results clearly indicate the economic and statistical success of the MOM (9) and, to a lesser extent, MOM (12) in predicting individual emerging markets currency returns.

Following existing studies (Brunnermeier et al., 2009; Burnside et al., 2011; Burnside et al., 2010; Lustig and Verdelhan, 2007; Li et al., 2015; Lustig et al., 2011; Verdelhan, 2018), we also assess the economic significance of our OOS forecasts using a portfolio allocation exercise. More specifically, we compute the net-of-transaction cost realized return on a portfolio formed based on the sign of the predicted return from model j as an equally weighted average of the net realized return in Eq. (19). We view the portfolio results as complementary to our profitability results at the individual currency level.

Table 8 presents the profitability for equally weighted portfolios for the models with fundamental and the technical indicators. For comparison, we also report the performance measures for three benchmark portfolios: the carry, momentum and $1/N$ portfolios. To form the carry portfolio, all currencies are sorted into six portfolios based on their lagged one-month forward premium $(f_{t-1} - s_{t-1})$ and then ranked from small to large forward premium. The carry portfolio goes long in the three portfolios with the highest lagged forward premium, and goes short in the three portfolios with the lowest lagged forward premium. The carry portfolio has been widely used in the literature (Lustig and Verdelhan, 2007; Lustig et al., 2011; Burnside et al., 2011; Burnside et al., 2010, Verdelhan, 2018) and is shown to be profitable for emerging markets currencies by Gilmore and Hayashi (2011).

To form the momentum portfolio, we sort the currencies into six portfolios based on their lagged one-month return (r_{t-1}) and then rank them from small to large lagged returns. The momentum portfolio goes long in the "winner" portfolios (the top three portfolios with the highest lagged return), and goes short in the "loser" portfolios (the bottom three portfolios with

Table 9
Statistical forecast accuracy of combination forecasts. The table provides the Out-of-Sample (OOS) statistical forecast accuracy for the combined forecast. 'Average' refers to the combination forecast constructed as the simple average of the MOM (9) and symmetric Taylor rule forecasts while 'Regression-based' is the regression-based combination forecast of the MOM (9) and symmetric Taylor rule forecasts. The table reports the *OOS* R^2, the MSE-F test of equal predictive accuracy of McCracken (2007), the Giacomini and White (2006) (GW) test of conditional predictive ability, the Clark and West (2007) (CW) test of equal predictive ability and Giacomini and Rossi (2010) (GR) fluctuations test. Positive *OOS* R^2 are in bold. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively. A GW statistic succeeded by (+) or (−) indicates, respectively, that the model statistically significantly outperforms or underperforms the random walk benchmark at the 10% level.

	Average	Regression-based		Average	Regression-based		Average	Regression-based
	CZK			HKD			HUF	
R^2_{OOS}	**0.05**	**0.06**	R^2_{OOS}	**0.02**	**0.15**	R^2_{OOS}	**0.05**	**0.05**
MSE-F	6.56***	7.35***	MSE-F	3.17**	18.81***	MSE-F	5.79***	6.41***
GW	1.88	1.69	GW	3.33	1.90	GW	2.47	1.78
CW	2.13**	2.21**	CW	2.06**	2.12**	CW	2.25**	2.13**
GR	2.07	2.17	GR	1.81	1.27	GR	2.90	2.42
	MXN			PHP			SGD	
R^2_{OOS}	**0.02**	**0.08**	R^2_{OOS}	**0.09**	**0.10**	R^2_{OOS}	**0.03**	**0.05**
MSE-F	2.85**	9.52***	MSE-F	11.77***	12.44***	MSE-F	3.66**	6.19***
GW	2.64	2.05	GW	5.12$^{(+)}$	3.50	GW	1.21	3.58
CW	1.53*	2.89***	CW	3.14***	3.11***	CW	1.51*	2.54***
GR	3.12*	1.40	GR	3.32**	3.17	GR	2.04	3.48**
	THB			TRY			TWD	
R^2_{OOS}	**0.02**	**0.06**	R^2_{OOS}	0.00	**0.04**	R^2_{OOS}	**0.05**	**0.05**
MSE-F	3.21**	7.07***	MSE-F	1.05	5.29***	MSE-F	6.15***	6.41***
GW	1.55	2.94	GW	0.79	2.81	GW	3.81	3.22
CW	1.54*	2.51***	CW	1.69**	2.64***	CW	2.41***	2.37***
GR	1.71	3.20**	GR	0.79	0.97	GR	2.30	2.07
	ZAR							
R^2_{OOS}	**0.05**	**0.06**						
MSE-F	6.43***	6.92***						
GW	7.30$^{(+)}$	4.27						
CW	2.87***	2.68***						
GR	4.28***	3.47**						

the lowest lagged return).[23] The performance of momentum portfolios have also been widely studied in existing research (Burnside et al., 2011, Menkhoff et al., 2012, Orlov, 2016). The third benchmark portfolio that we consider is the $1/N$ portfolio of DeMiguel et al. (2009) which equally weights all the currencies. The returns on the $1/N$ portfolio are equivalent to averaging the returns of a buy-and-hold strategy (i.e., to the average unconditional return) for all the currencies.

Several interesting findings emerge from Table 8. First, consistent with our results for the individual currencies in Tables 6 and 7, our portfolio results again indicate the success of the momentum and relative strength index portfolios in producing positive and statistically significant (at the 5% level or better) net-of-transaction costs returns. The performance of the MOM (9) portfolio, in particular, is striking given that the net returns on the MOM (9) portfolio are larger than those of the benchmark portfolios and, in particular, the widely studied carry portfolio. In addition, the excess kurtosis of the MOM (9) is smaller than that of the carry portfolio. It is also important to note that the risk-adjusted returns on the momentum and relative strength index portfolios are larger than those of the three benchmark portfolios. In contrast to the success of the momentum portfolio, our results suggest a diminished performance of the two Taylor rules at the portfolio level relative to the individual currency results. In fact, the average net returns on the two strategies are positive but insignificant and are lower than those of the carry portfolio. The returns on Taylor rule portfolios is likely weighted down by the some of negative realized returns on the Taylor rule at the individual currency level.

In sum, we view that the economic significance results corroborate our statistical forecast accuracy results. In specific, trading individual currencies on the sign of the predicted returns from the MOM (9) and TR_s generates positive and significant profits. At the portfolio level, the MOM (9) net and risk-adjusted returns are larger than those of the benchmark portfolios whereas the profitability of the TR_s is weakened.

[23] Following Li et al. (2015) and Anatolyev et al. (2017), we also experiment with "three-long and three-short" carry and momentum portfolios. The "three-long and three-short" carry portfolio assumes that the investor goes long in the three currencies with the largest lagged forward premium and short in the three currencies with the smallest lagged forward premium. The "three-long and three-short" momentum portfolio assumes that the investor goes long in the three currencies with the largest lagged return and short in the three currencies with the smallest lagged return. When we employ the "three-long and three-short" portfolios, our results are qualitatively similar to those reported in the paper in that the benchmark portfolios consistently underperform the Taylor rule, MOM (9) and relative strength index portfolios in terms of net and risk-adjusted returns.

Table 10
Economic evaluation of combination forecasts. The table provides the profitability results from trading based on the sign of the combination forecasts. 'Average' refers to combination forecast constructed as the simple average of the MOM (9) and symmetric Taylor rule forecasts while 'Regression-based' is the regression-based combination forecast of the MOM (9) and symmetric Taylor rule forecasts. The table reports the annualized average net-of-transaction costs realized returns, standard deviation, skewness, excess kurtosis, Sharpe and Sortino ratios. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Average	Regression-based		Average	Regression-based		Average	Regression-based
	CZK			HKD			HUF	
Mean	7.47*	6.76	Mean	0.24*	0.45***	Mean	11.39**	12.83**
Std. Dev.	13.05	13.09	Std. Dev.	0.40	0.39	Std. Dev.	16.42	16.33
Skewness	0.04	0.06	Skewness	−0.46	0.97	Skewness	0.60	0.94
Excess Kurtosis	1.05	1.03	Excess Kurtosis	5.16	4.32	Excess Kurtosis	3.33	3.03
Sharpe Ratio	0.57	0.52	Sharpe Ratio	0.59	1.16	Sharpe Ratio	0.69	0.79
Sortino Ratio	0.88	0.80	Sortino Ratio	0.71	1.90	Sortino Ratio	1.08	1.47
	MXN			PHP			SGD	
Mean	11.29***	10.80***	Mean	6.32***	6.17***	Mean	4.90**	5.50**
Std. Dev.	12.15	12.19	Std. Dev.	5.42	5.43	Std. Dev.	6.58	6.54
Skewness	0.48	0.42	Skewness	−0.29	−0.26	Skewness	0.25	0.32
Excess Kurtosis	2.26	2.32	Excess Kurtosis	0.33	0.28	Excess Kurtosis	2.23	2.19
Sharpe Ratio	0.93	0.89	Sharpe Ratio	1.17	1.14	Sharpe Ratio	0.74	0.84
Sortino Ratio	1.44	1.39	Sortino Ratio	1.71	1.69	Sortino Ratio	1.11	1.30
	THB			TRY			TWD	
Mean	5.83***	5.56***	Mean	13.87***	13.54***	Mean	4.52***	4.52***
Std. Dev.	5.31	5.34	Std. Dev.	12.70	12.73	Std. Dev.	5.12	5.12
Skewness	−0.11	0.06	Skewness	1.06	1.01	Skewness	0.38	0.38
Excess Kurtosis	0.07	−0.16	Excess Kurtosis	3.90	3.93	Excess Kurtosis	0.56	0.56
Sharpe Ratio	1.10	1.04	Sharpe Ratio	1.09	1.06	Sharpe Ratio	0.88	0.88
Sortino Ratio	1.80	1.90	Sortino Ratio	2.40	2.21	Sortino Ratio	1.66	1.66
	ZAR							
Mean	15.49***	16.88***						
Std. Dev.	15.75	15.63						
Skewness	0.63	0.66						
Excess Kurtosis	1.19	1.14						
Sharpe Ratio	0.98	1.08						
Sortino Ratio	1.96	2.26						

6.3. Forecast combination

As discussed earlier, economists have closely scrutinized the predictive power of the major models of exchange rate determination whereas currency traders have widely used technical analysis in the currency markets. Given that our results suggest that the informational content of models with fundamental variables and technical trading signals is of predictive value, a natural next step is to combine the forecasts of the MOM (9) and TR_s, our two best performing models. By doing so, we exploit the informational content of both forecasts and thereby avoid examining each in isolation as practitioners and academics have traditionally done.

From a statistical perspective, combining forecasts is desirable for several reasons (Timmermann, 2006). First, it is often difficult to identify the best-performing model so that combining forecasts provides diversification gains. Second, the combined forecast is more robust to structural breaks in the individual forecasting models. Third, given that every model is likely to be misspecified, combining forecasts will alleviate the effects of misspecification in individual forecasting models (Elliott and Timmermann, 2016). From an empirical perspective, Timmermann (2006) outlines the success of combined forecasts in predicting macroeconomic and financial variables.

We consider two simple combinations of the forecasts of our best performing models. The first is a simple average of the MOM (9) and TR_s forecasts. Namely, we construct the combined forecast as: $\Delta\widehat{s}_{t+1}^{COMB1} = 0.5 \times \Delta\widehat{s}_{t+1}^{TR_s} + 0.5 \times \Delta\widehat{s}_{t+1}^{MOM(9)}$. The advantage of using a simple average of the two forecasts is to circumvent estimation error since the combination weights are imposed rather than estimated (Elliott and Timmermann, 2016).

The second method that we employ to combine our two best-performing forecasts is a regression-based combination approach in which the currency return is regressed on the forecasts to generate the optimal combination weights:

$$\Delta s_{t+1} = \beta_0 + \beta_1 \Delta\widehat{s}_{t+1}^{TR_s} + \beta_2 \Delta\widehat{s}_{t+1}^{MOM(9)} + \upsilon_{t+1}. \qquad (20)$$

The regression-based combination forecast is the fitted value from Eq. (20). While it is common in the existing literature to impose the restriction that the coefficients β_1 and β_2 sum to one and to exclude the intercept, β_0, Diebold (2015) notes that it is preferable, in practice, not to impose the restriction $\beta_1 + \beta_2 = 1$ and to include an intercept in the regression for bias correction.

Tables 9 and 10 present, respectively, the OOS forecast accuracy and economic significance results for the combined forecasts. The excellent OOS performance and profitability of the combined forecasts are immediately evident from Tables 9 and 10. In fact, with the exception of the simple average combination forecast for TRY, the R^2_{OOS} is positive and significant for the combined forecasts of all the currencies at the 10% level or higher. In addition, with the exception of the simple average combination forecast for TRY, the *MSE-F* statistic indicates that the combined forecasts for all the currencies exhibit an OOS performance that is superior to that of the random walk at the 5% level or higher. The GW test results provide evidence that the conditional predictive ability of the simple average combination forecast for PHP and ZAR is superior to that of the random walk at the 10%.

The economic significance results, presented in Table 10, echo the strong evidence of the superior OOS predictive ability of the combined forecasts. With the exception of the regression-based combination forecast for CZK, the mean net returns are positive and significant, at the 10% level or higher, for all the currencies. The Sharpe ratios of the net returns of the combined forecasts are larger than, or comparable to, those of the MOM (9) for all currencies except CZK and HKD. In sum, we view our results as providing strong evidence of the superior predictive performance and economic significance of the combined forecasts.

7. Conclusion

We provide an in-depth analysis of the predictive ability of models with fundamentals and technical indicators for emerging market currencies. Our findings suggest that the forecasts from the symmetric Taylor rule as well as from a predictive regression exploiting the informational content of the momentum indicator generate statistically superior out-of-sample forecasts.

We assess the economic significance of the out-of-sample forecasts using a trading strategy which exploits the sign of the predicted currency return. Our results indicate that trading individual currencies based on the sign of the predicted return from the predictive regression with the momentum trading signals as an independent variable as well as the symmetric Taylor rule generates positive, statistically significant and larger net-of-transaction cost and risk-adjusted returns than any of the competing forecasts. Portfolios that are constructed based on the sign of the predicted returns from the predictive regression with the momentum indicator outperform the widely studied benchmark portfolios such as carry, momentum and *1/N* benchmark portfolios. We combine the forecasts from the two best performing models using simple techniques and find that the combination forecasts also exhibit superior predictive accuracy and produce large risk-adjusted and net-of-transaction costs returns.

We view the profitability of the momentum indicator as consistent with the existence of discernable and profitable trends in emerging markets exchange rates. The success of the symmetric Taylor rule in predicting emerging markets currency returns is also indicative that fundamentals, such as the output gap and inflation differential, possess predictive power for emerging markets currency returns.

Our findings have important policymaking and practical implications. From a practical perspective, our results suggest that investors can use fundamental and technical information to detect and profitably exploit trends in emerging markets currencies. From a policymaking perspective, our findings are useful for a more complete understanding of the drivers of exchange rate fluctuations for the central bankers in emerging markets.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2019.04.002.

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