European and Non-European Emerging Market Currencies: Forward Premium Puzzle and Fundamentals

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The empirical literature has consistently rejected that the uncovered interest parity (UIP) theorem holds in practice, thus posing the well-known forward premium puzzle. In this study, we examine this issue for a sample of 18 emerging market currencies and, in addition, for a subsample of 6 currencies from emerging Europe. We first confirm earlier evidence for the existence of a forward premium puzzle for emerging market economies. We then extend the model with a view to exploring systematic relationships between excess returns from investments in foreign currency and country-specific economic fundamentals. Subsequently, we use this extended model to generate out-of-sample forecasts of currency returns. We also test for forecast accuracy, confirming that these forecasts are superior to naïve forecasts. Our results show that investments based on these forecasts generate considerably higher returns than alternative investment strategies. This applies in particular to our full sample of 18 emerging market currencies. For the subsample of 6 currencies from emerging Europe, profits per trade for the model-based forecasts also outperform those generated by the other investment strategies, but by a smaller margin. These results suggest that, compared with currencies of advanced countries, the smaller bias in the forward exchange rates of emerging market currencies found in the empirical literature could relate to the better predictability of currency returns for emerging market currencies.

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1 Introduction

Uncovered interest rate parity (UIP) implies that international differentials in yield levels reflect expectations about exchange rate changes. However, the empirical literature (e.g. Fama, 1984) has consistently rejected that this theorem holds in practice, thus posing the well-known forward premium puzzle, which is sometimes also labeled forward bias puzzle. In fact, the empirical literature finds that, on average, high-yielding currencies tend to depreciate far less than suggested by forward premiums and might even appreciate. In the latter case, the forward discount actually points in the wrong direction, which is often found to be true for advanced economies. Thus, on empirical grounds, forward exchange rates cannot be considered to be unbiased predictors of future exchange rates. Frequently, this discrepancy between economic theory and empirical findings is ascribed to time-varying risk premiums. Other explanations that have been put forward relate to participation constraints and nominal price rigidities. However, as Sarno, Valente and Leon (2006) put it, "even with the benefit of [more than] 20 years of hindsight, the forward bias puzzle has not been convincingly explained and continues to baffle the international finance profession."

In this study, we revisit this issue for a sample of 18 emerging market currencies and, in addition, for a subsample of 6 currencies from emerging Europe, with

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a view to exploring whether there are systematic differences between trades in these currencies and in emerging market currencies in general. In the analysis, we also test for violations of UIP by focusing on excess returns from investments in foreign currency. We extend the model to explore whether there is a systematic relationship between excess returns and country-specific economic fundamentals. We then use this extended excess return model to generate forecasts of currency returns, raising the question of whether investments based on these forecasts generate higher returns than investments in an evenly weighted basket of emerging market currencies or under a simple carry trade strategy. Finally, we relate our results to the question of possible reasons for differences in the bias in forward exchange rates.

2 Literature Survey

The first empirical studies that explored the forward premium puzzle focused on advanced economies.[2] Apart from finding ample empirical evidence that would reject UIP, some of these early papers – including Bilson (1981) and Fama (1984) – also examined this issue from the angle of foreign exchange excess returns and found some evidence for their predictability, which again is inconsistent with UIP. More recently, Sarno, Valente and Leon (2006) found evidence for nonlinearities in the relationship between spot and forward exchange rates. In a single exchange rate setting, they found statistically significant and persistent deviations from UIP when Sharpe ratios (the expected excess returns per unit of risk) were small, while UIP held in the context of larger Sharpe ratios. Following Lyons' (2001) limits to speculation hypothesis, they rationalized this finding by arguing that financial institutions do not have an incentive to make foreign currency investments with Sharpe ratios that are below buy-and-hold equity strategies (which in the United States had historically realized Sharpe ratios of 0.4).

Until the 1990s, data scarcity did not allow economists to examine this issue also for emerging markets. However, more recently, the increasing liberalization of foreign exchange and money markets has enabled researchers to extend the analysis of the bias of forward exchange markets to include emerging market economies.

A first seminal paper taking this approach is by Bansal and Dahlquist (2000), who compared the size of the forward bias in emerging and developed economies and found considerable cross-sectional differences in the extent of the forward bias. As investments in emerging markets are considered to be more risky, the presence of a time-varying risk premium in forward exchange rate markets should result in a larger bias for emerging markets. However, the findings of Bansal and Dahlquist (2000) suggest exactly the opposite: Forward exchange rates in emerging markets are found to be less biased than forward exchange rates in advanced economies. In fact, in the latter, the forward premium puzzle is found to be present when U.S. interest rates exceed foreign interest rates. There is no evidence, in turn, for such state dependence in emerging market economies.

Bansal and Dahlquist (2000) also show empirically that the size of the forward bias is systematically related to macroeconomic variables, such as GDP per capita,

[2] *For a listing of the most important of these earlier papers, see Sarno, Valente and Leon (2006) and Bansal and Dahlquist (2000).*

inflation levels and inflation volatility. Thus, the lower bias of the forward market in emerging currencies seems to arise from the better predictability of emerging market exchange rates.

Frankel and Poonawala's findings (2004) support this view. In this paper as well, emerging market forward exchange rates are shown to be less biased than those of developed countries. Frankel and Poonawala therefore concluded that time-varying risk premiums might not explain traditional findings of a bias. They instead ventured that emerging market currencies probably have more discernible exchange rate trends than currencies of advanced countries.

3 Dataset and Estimation Strategy

In this paper, we take the analysis of forward exchange rates in emerging markets one step further by examining whether it is possible to identify systematic factors that drive exchange rates in emerging economies and thus contribute to lower forward biases. Moreover, we investigate whether the inclusion of such systematic factors can be used to improve returns on investments in emerging market currencies.

The sample used in this study covers the period from June 1994 to February 2008 and includes 18 emerging market economies. Furthermore, we conduct a complementary analysis on a subsample of 6 countries from emerging Europe.[3] Complete data coverage (all countries) is available from June 1997. The data used have a monthly frequency. For a detailed description of the data sources, see table A in the annex.

In a first stage of the empirical analysis, we apply the standard Fama (1984) test of UIP to the underlying data sample by estimating a regression of the form:

$$\Delta s_t = \alpha + \beta\,(f_{t-1} - s_{t-1}) + u_t \tag{1}$$

where Δs_t stands for the change in the spot exchange rate, f_{t-1} for the forward rate at time $t\text{-}1$ and u_t for the statistical disturbance term (variables in logs). We thus revisit the question of whether we find a forward bias for our sample, i.e. an estimate for β that is significantly less than 1. The presence of a forward bias would imply that this violation of UIP results in profits from investing in foreign currency.

In order to explore this question further, we reparameterize equation (1) to test for deviations from UIP by focusing on excess returns ER_t from investments in foreign currency:

$$ER_t = \alpha + (\beta - 1)\,(f_{t-1} - s_{t-1}) + u_t \tag{2}$$

The excess return variable consists of the combined interest rate differential and the exchange rate change that is associated with investing in a foreign currency compared with a risk-free investment in the domestic currency. Given the world-

[3] *The 18 countries of the full sample are Brazil, Chile, Colombia, the Czech Republic, Hungary, Indonesia, Israel, Korea, Mexico, the Philippines, Poland, Romania, Russia, South Africa, Slovakia, Taiwan, Thailand and Turkey. The 6 countries contained in the subsample are the Czech Republic, Hungary, Poland, Romania, Russia and Slovakia.*

wide spectrum of the sample, we took the U.S. dollar as the domestic currency. The excess returns are calculated by using the forward exchange rate and the (nominal) spot rate (both in logs).

If UIP were to hold, the term $(\beta-1)$ would be zero and there would be no (predictable) excess returns from investments in foreign currencies. Frankel and Poonawala's (2004) findings of a β which is significantly different from 1 but larger than in developed countries suggests there might be scope for the inclusion of other systematic factors that are able to improve excess returns further. We address this issue by adding the year-on-year changes in foreign exchange reserves r, the short-term U.S. interest rate i and the CRB (Commodity Research Bureau's commodity price) index crb to equation (3). The inclusion of the CRB index is motivated by the reliance of many emerging markets on commodity exports. These variables have to be sufficiently lagged to be of use not only for explaining excess returns but also for generating forecasts. Moreover, in line with the limits to speculation hypothesis, a variable capturing the Sharpe ratio (Sh) is included in the equation, which takes the actual value of the Sharpe ratio (excess returns divided by volatility, as expressed by annualized standard deviation) if its three-month moving average is higher than 0.7, and a value of 0 in all other cases. This results in equation (3):

$$ER_t = \alpha + \underset{(+)}{(\beta-1)} (f_{t-1} - s_{t-1}) + \underset{(+)}{\gamma} r_{t-1} + \underset{(-)}{\delta} i_{t-1} + \underset{(+)}{\mu} crb_{t-1} + \underset{(-)}{\varphi} Sh_{t-1} + u_t \qquad (3)$$

We again examine whether these additional variables are correctly signed and significant.

In a next step, equation (3) is used to generate out-of-sample forecasts of excess returns for the period $t+1$ for the panel of the 18 currencies included in the sample, starting with the sample period June 1994 to June 1997. Two variants were investigated: (1) forecasts with rolling 37-month periods and (2) forecasts based on growing sample sizes as from June 1997 (i.e. observations were subsequently added across time). Variant (2) is not reported here, as variant (1) proved to be more profitable (in terms of cumulative excess returns).

If the excess return forecast for a given currency exceeds the median forecast, this currency is selected for inclusion in an equally weighted basket. As in Boothe and Glassman (1987), we calculate total profits for the model-based forecasts. We then compare the performance of this basket with the average performance of all 18 currencies as well as with the performance of a simple carry trade basket comprising the 9 highest yielding currencies. The baskets are rebalanced on a monthly basis. If the excess return forecast for a particular currency falls below the median, this currency is dropped from the basket. The same is true for the carry basket if the interest rate differential of a currency falls below the median.

In addition, since the model also provides for counting of the number of trades, it allows us to check whether the excess returns per trade are sufficient to cover the transaction costs.

Finally, we also check formally for the statistical quality of our model-based excess return forecasts by employing a series of Diebold-Mariano tests. In essence, this is a test of predictive accuracy which verifies whether the loss differential of two competing predictions is zero by using a long-run estimate of the variance of the difference series (see Diebold and Mariano, 1995). In line with standard practice, we compare our model-based forecasts with a naïve forecast based on a simple forecasting rule, namely that the performance forecast for a given period is equal to the realized performance of the preceding period.

4 Estimation Results and Interpretation

4.1 Full Emerging Market Sample

Applying the standard Fama test of UIP to the underlying (full) data sample produces an estimate for β that is significantly smaller than 1, but greater than zero for the panel as a whole (see table 1). Thus, we find evidence of a bias in forward exchange rates of emerging market economies, albeit not a particularly large one. This finding confirms the results reported by Bansal and Dahlquist (2000) and by Frankel and Poonawala (2004).

The Fama tests for individual countries seem to be strongly influenced by the currency crises that occurred in Russia in 1998 and in Southeast Asia in 1997 and 1998 (see the coefficient estimates reported in table 2).

Table 1

Fama Test Results (Full Sample)

Variable	Coefficient	Standard error	t-statistic	Probability
Constant	−0.001715	0.001	−2.026278	0.043
$(f_{t-1} - s_{t-1})$	0.649	0.112	5.804	0.000

Source: Authors' calculations.

Note: Dependent variable: DLOG(st); method: pooled least squares; sample: June 1997 to February 2008; included observations: 129; cross-sections included: 18; total pool (balanced observations): 2,322. White diagonal standard errors and covariance (d.f. corrected).

Table 2

Fama Test Results (Individual Countries)

Country	Variable	Coefficient	Standard error	t-statistic	Probability
Brazil	$(f_{t-1} - s_{t-1})$	0.125	1.055	0.118	0.906
Chile	$(f_{t-1} - s_{t-1})$	−2.648	1.642	−1.613	0.109
Colombia	$(f_{t-1} - s_{t-1})$	1.100	0.419	2.624	0.010
Czech Republic	$(f_{t-1} - s_{t-1})$	0.573	0.861	0.666	0.507
Hungary	$(f_{t-1} - s_{t-1})$	0.789	0.825	0.956	0.341
Indonesia	$(f_{t-1} - s_{t-1})$	−0.822	1.096	−0.749	0.455
Israel	$(f_{t-1} - s_{t-1})$	0.786	0.743	1.059	0.292
Korea	$(f_{t-1} - s_{t-1})$	0.470	1.333	0.353	0.725
Mexico	$(f_{t-1} - s_{t-1})$	−0.302	0.422	−0.716	0.475
Philippines	$(f_{t-1} - s_{t-1})$	1.581	0.714	2.213	0.029
Poland	$(f_{t-1} - s_{t-1})$	1.053	0.569	1.851	0.067
Romania	$(f_{t-1} - s_{t-1})$	0.573	0.114	5.045	0.000
Russia	$(f_{t-1} - s_{t-1})$	2.643	0.397	6.666	0.000
South Africa	$(f_{t-1} - s_{t-1})$	−2.802	1.350	−2.075	0.040
Slovakia	$(f_{t-1} - s_{t-1})$	0.936	0.490	1.910	0.058
Thailand	$(f_{t-1} - s_{t-1})$	1.498	0.854	1.756	0.082
Turkey	$(f_{t-1} - s_{t-1})$	0.816	0.212	3.843	0.000
Taiwan	$(f_{t-1} - s_{t-1})$	−1.361	1.078	−1.262	0.209

Source: Authors' calculations.

As a result, some of the country-specific coefficients take on rather extreme values and are thus hard to interpret. In order to achieve more robust coefficient estimates we continue the analysis in a panel setting.[4]

As to the question of whether there is a systematic relationship between the development of the spot exchange rate and (lagged) economic variables, our empirical analysis yields results in which all but one of the explanatory variables that capture economic fundamentals are correctly signed and statistically significant at the 5% level (see table 3). In particular, rising foreign exchange reserves and a higher nominal interest rate differential have a positive effect on excess returns. The only variable that does not confirm our priors is the Sharpe ratio. Based on our dataset, we thus cannot confirm that a high Sharpe ratio in the preceding months has a statistically significant negative impact on excess returns. However, as the Sharpe ratio failed only slightly to reach statistical significance (at the 10% level) after the White-correction, we kept this variable in our base regression and also in the forecast setting.

The panel estimation was specified without random or fixed effects (i.e. as a pooled least square estimation with a single constant and no cross-section effects), because for some countries the Sharpe ratio never exceeds the threshold value and is therefore set at zero, as explained in section 3. This precludes a model with random effects. We tested for the null hypothesis of redundant cross-section fixed effects, which was not rejected. We also implemented the White-test for heteroskedasticity, regressing the squared residuals of the pooled least square regression on all explanatory variables as well as squared explanatory variables. This test rejected the null hypothesis of homoskedasticity and we thus used White heteroskedasticity-consistent standard errors.

Table 3

Fundamentals and Performance (Full Sample)

Variable	Coefficient	Standard error	t-statistic	Probability
r_{t-1}	0.009	0.004	2.041	0.041
$(f_{t-1} - s_{t-1})$	0.560	0.101	5.541	0.000
Sh_{t-1}	−0.012	0.008	−1.518	0.129
i_{t-1}	−0.003	0.000	−6.155	0.000
crb_{t-1}	0.00006	0.00001	4.533	0.000
Constant	−0.006	0.004	−1.515	0.130

Source: Authors' calculations.

Note: Dependent variable: ER_t; method: pooled least squares; sample: June 1994 to February 2008; included observations: 165; cross-sections included: 18; total pool (unbalanced observations): 2,716. White diagonal standard errors and covariance (d.f. corrected).

It should be noted that we also tried to control for differences in growth dynamics by including industrial production as an explanatory variable. Our results (not reported in detail here) show that industrial production lagged by one period is highly significant in explaining excess returns, i.e. strong real-sector

[4] *See Hsiao (2003) for information on the usefulness of panel regressions in addition to country-specific regressions.*

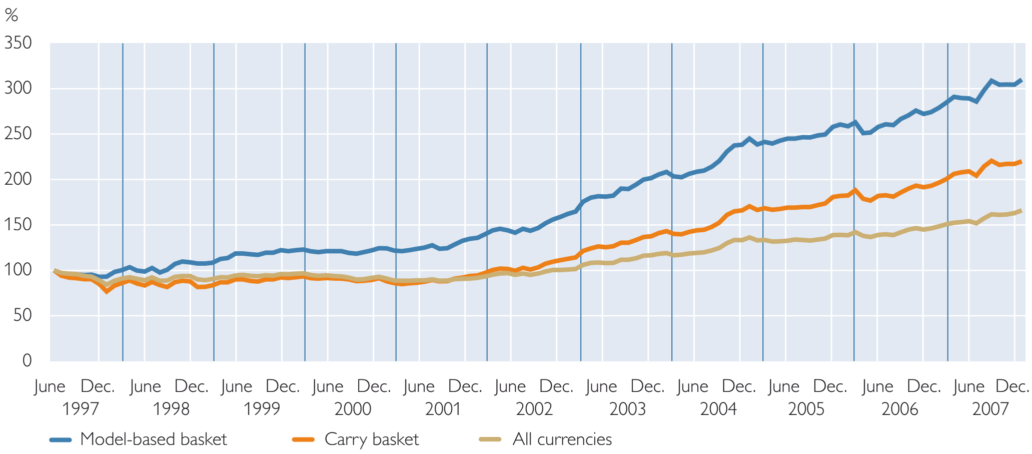
activity has a positive effect on returns, while industrial production with more lags does not have a significant impact on returns. However, we cannot use industrial production lagged by one period for forecasting purposes based on real-time data, given the lags in data publication. Yet, we are in a position to use foreign exchange reserves, lagged by one period, for forecasting purposes, as the publication lag for reserves is shorter and several central banks make such data available on a weekly basis.

For out-of-sample forecasts, we report rolling period forecasts (37 months) as indicated above. We also find that the estimates for the coefficients are rather unstable in different sampling periods, which would help explain why the forecasts based on the rolling 37-month samples did better than the forecasts based on growing sample sizes. More specifically, the sampling period is characterized by two rather distinct periods for currency returns: From June 1997 to December 2001, the average excess returns (for all 18 currencies) were negative, whereas between January 2002 and February 2008, they rose to a striking 10.3%. For the whole sample period of June 1997 to February 2008, the excess returns amounted to 4.86%. Nevertheless, the model appears to capture these changing dynamics quite well: The model-based forecasts are not only able to generate returns that exceed the average of all currencies, but also to outperform the carry basket. The cumulative excess returns for the forecasting period of June 1997 to February 2008 amount to 66% for all currencies, 120% for the carry basket and 210% for the model-based forecasts (see chart 1).

For the entire observation period, the carry basket produces 183 rebalancing trades, while the model generates 266 trades (i.e. for one-ninth of the portfolio in both cases). As the profits per trade for the model-based forecasts (54 basis points) are markedly higher than those for the simple carry strategy (30 basis points), introducing the trading costs would not alter the qualitative result of outperformance of the model-based strategy relative to the carry strategy. We do not include trading costs in our calculations as market participants may face different transaction costs. However, 54 basis points of profits per trade should easily suffice to

Chart 1

Cumulative Excess Returns of Different Investment Strategies (Full Sample)



Source: Authors' calculations.

Table 4

Diebold-Mariano Test Results (Full Sample)
Forecasting period from
July 1997 to February 2008

Country	Diebold-Mariano test statistic	p-value
Brazil	−1.902	0.059
Chile	−2.734	0.007
Colombia	−2.038	0.044
Czech Republic	−3.126	0.002
Hungary	−3.691	0.000
Indonesia	−0.946	0.346
Israel	−2.668	0.009
Korea	−1.083	0.281
Mexico	−3.448	0.001
Philippines	−2.800	0.006
Poland	−3.218	0.002
Romania	−2.047	0.043
Russia	0.030	0.976
South Africa	−3.313	0.001
Slovakia	−3.188	0.002
Thailand	−2.345	0.021
Turkey	−2.540	0.012
Taiwan	−1.769	0.079

Source: Authors' calculations.

Note: To reject the null hypothesis of equal predictive accuracy at the 5% level, the absolute value of the D-M test statistic has to be larger than 1.96. The test was conducted against a naïve forecasting rule (performance forecast for t+1 = realized performance at time t).

cover such costs; Lyons (2001) estimates the trading costs for major world currencies at 10 basis points. Major world currencies are generally more liquid than emerging market currencies, but the liquidity of foreign exchange markets has risen since 2001.

As to the Diebold-Mariano tests, the null hypothesis of equal accuracy is rejected in most cases at the 5% significance level. Thus, the results of these tests confirm the superior accuracy of the model-based forecasts compared with naïve forecasts for most country cases (see table 4).

The investment strategy with the standard investment rule ("long only") provides higher returns than the strategy with the modified investment decision rule ("short/long"). As there are positive excess returns for the basket of all 18 countries, funding in emerging market currencies is more expensive than funding in U.S. dollars (which is implicitly assumed in the "long only" strategy). This explains the better performance of the "long only" strategy.

These results lend support to the idea that the smaller bias in forward exchange rates of emerging market currencies compared with currencies of advanced countries could relate to the better predictability of currency returns for emerging market currencies.

4.2 European Emerging Market Currency Subsample

Repeating our estimation procedure for the subsample of 6 currencies from emerging European economies yields the following results. In terms of the interaction between exchange rates and economic fundamentals, the empirical results for the subsample are similar to those for the full sample. Again, all explanatory variables are correctly signed. Moreover, all but one variable are statistically significant (again, the Sharpe ratio is not statistically significant). Compared with the full sample, the coefficient estimates in the emerging Europe subsample for foreign exchange reserves, the interest rate differential and commodity prices are larger and thus economically more significant than in the full sample.

In line with the above-mentioned forecasting strategy, we employ rolling 37-month periods for the out-of-sample forecasts. As in the case of the full sample, the model-based forecasts for the subsample generate returns that exceed the average of all currencies, but also outperform the carry basket. The cumulative excess returns for the forecasting period amount to 120% for all currencies and

Table 5

Fundamentals and Performance (Subsample)

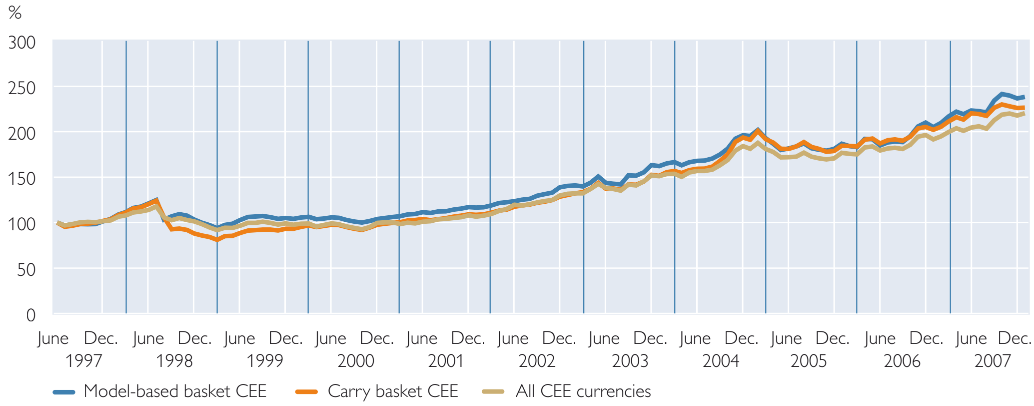
Variable	Coefficient	Standard error	t-statistic	Probability
r_{t-1}	0.011	0.005	2.076	0.038
$(f_{t-1} - s_{t-1})$	0.625	0.167	3.749	0.000
Sh_{t-1}	−0.014	0.010	−1.417	0.157
i_{t-1}	−0.003	0.001	−4.342	0.000
crb_{t-1}	0.00008	0.00002	3.701	0.000
Constant	−0.010	0.007	−1.568	0.117

Source: Authors' calculations.

Note: Dependent variable: ER_i; method: pooled least squares; sample: June 1994 to February 2008; included observations: 165; cross-sections included: 6; total pool (unbalanced observations): 886. White diagonal standard errors and covariance (d.f. corrected).

Chart 2

Cumulative Excess Returns of Different Investment Strategies (Subsample)



Source: Authors' calculations.

Table 6

Diebold-Mariano Test Results (Subsample) Forecasting period from July 1997 to February 2008

Country	Diebold-Mariano test statistic	p-value
Czech Republic	−3.378	0.001
Hungary	−3.459	0.001
Poland	−3.495	0.001
Romania	−2.587	0.011
Russia	−0.028	0.978
Slovakia	−3.330	0.001

Source: Authors' calculations.

Note: To reject the null hypothesis of equal predictive accuracy at the 5% level, the absolute value of the D-M test statistic has to be larger than 1.96.

to 126% for the carry basket, while they reach 138% for the model-based forecasts (see chart 2).

Compared with the full sample, for the emerging Europe subsample the number of trades generated by the model falls to 117. The profits per trade for the model-based forecasts are lower for the subsample (15 basis points) than in the case of the full sample (54 basis points). At the same time, the profits per trade for the model-based forecasts turn out to be higher than those for the simple carry strategy (7 basis points), but are rather small in absolute terms and thus provide a relatively small cushion to cover the trading costs.

For the emerging Europe subsample, too, the results of the Diebold-Mariano tests confirm the superiority of the model-based forecasts compared with a naïve forecast for all countries but Russia (see table 6).

5 Summary and Conclusions

In this paper, we revisited the forward bias puzzle for a sample of 18 emerging market economies for the period of June 1994 to February 2008. Using the standard Fama (1984) test of uncovered interest rate parity, we first confirm the findings of previous empirical papers showing evidence for the existence of a forward bias puzzle for emerging market economies. We then extend the model with a view to exploring systematic relationships between excess returns from investments in foreign currency and country-specific economic fundamentals. Subsequently, we use this extended model to generate out-of-sample forecasts of currency returns. We also test for forecast accuracy, confirming that these forecasts are superior to naïve forecasts.

Our results show that investments based on these forecasts generate considerably higher returns than investments in an evenly weighted basket of emerging market currencies and they also outperform the returns resulting from a simple carry trade strategy. This holds both for the full sample of 18 emerging market currencies and for a subsample representing 6 currencies from emerging Europe. The cumulative excess returns for the forecasting period (June 1997 to February 2008) amount to 66% for the evenly weighted basket, 120% for the carry basket and 210% for the model-based forecasts. For the subsample, the model-based forecasts yield cumulative excess returns of 138%, compared with 120% for all currencies and 126% for the carry basket.

Among other things, these results suggest that the smaller bias in forward exchange rates of emerging market currencies compared with currencies of advanced countries found in the empirical literature on the forward bias puzzle could relate to the better predictability of currency returns for emerging market currencies in general and, more specifically, for the currencies of emerging European countries.

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Annex

Table A

Data Sources

Variable	Explanation	Source
r	Gross official reserves minus gold in USD million, year on year	Datastream
$f_{t-1} - s_{t-1}$	Log 1-month forward rate – log spot rate (forward rate calculated from interest rate differential)	Authors' calculations based on Bloomberg (exchange rates, 1-month interest rates CZ, HU, ID, IS, PH, PL, TK, TW), Datastream (1-month interest rates BR, CO, CL, KO, MX, RO, RU, SA, SK, TH)
Sh_{t-1}	Sharpe ratio	Authors' calculations based on Bloomberg (exchange rates, 1-month interest rates CZ, HU, ID, IS, PH, PL, TK, TW), Datastream (1-month interest rates BR, CO, CL, KO, MX, RO, RU, SA, SK, TH)
i_{t-1}	U.S. 1-month interbank rate	Bloomberg
crb_{t-1}	CRB commodity index	Bloomberg
ER_t	Excess returns	Authors' calculations based on Bloomberg (exchange rates, 1-month interest rates CZ, HU, ID, IS, PH, PL, TK, TW), Datastream (1-month interest rates BR, CO, CL, KO, MX, RO, RU, SA, SK, TH)