A simple forecasting rule for exchange rates in Emerging Markets *

Gonzalo Huertas
International Monetary Fund

Mateo Fernandez
Universidad de San Andres

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Abstract

Nominal exchange rates in Emerging Markets follow a predictable path over the long-run: they adjust to close the real exchange rate's deviation from its historical norm. Using machine learning methods, we introduce a Self-Calibrating Half-life Model (SCHL) that is able to predict exchange rate movements in Emerging Markets better than a random walk, direct forecasting methods, and a standard half-life model. Its predictions can be summarized in a simple rule of thumb: a country's currency moves to reduce one tenth of the real exchange rate's deviation from its historical norm in 9 months, and a quarter of that deviation in two years. Consistent with recent findings in the literature for advanced economies, we corroborate that the predictive power of exchange rate models in Emerging Markets depends on whether they follow an inflation targeting regime.

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1 Introduction

Until very recently, the dominant view in the macroeconomics literature had been that exchange rates follow a random walk, making their movements essentially unpredictable. The models of the seventies, eighties and nineties performed poorly out of sample, and economic fundamentals seemed to have little to say on exchange rate forecasts. But this narrative has begun to change, with recent research showing that macroeconomic variables –interest rates, inflation differentials, and global risk aversion– hold significant predictive power for predicting movements in advanced economies' currencies, both at long and short-term horizons, thanks in no small part to the advent of credible inflation targets.

This paper shifts the focus to Emerging Markets. We extend recent advances in the fundamentals-based forecasting literature and introduce a machine learning-optimized method, the Self Calibrating Half-Life (SCHL) model, which outperforms the random walk and other common forecasting approaches. We then provide a simple rule of thumb: just as in Advanced Economies, Emerging Market (EM) currencies slowly adjust to close the deviation of their countries' real exchange rates from the historical norm. Over a nine month period, this gap closes by about ten percent; after two years, exchange rate adjustment will have closed the gap by about a quarter.

We arrive at the above rule of thumb by building on the half-life model in Zorzi and Rubaszek (2020), enhancing the approach by using machine learning to determine the optimal horizon for the real exchange rate's regression to the mean, which, in an Emerging Market context, turns out to be significantly longer than the standard value for advanced economies. We show that the forecasts from our approach outperform a random walk, direct forecast models, and the standard half-life model.

The fact that advanced economy forecasting methods work just as well in EMs may come as a surprise, given that these countries feature more volatile macroeconomic environments, shallower foreign exchange markets, and a much shorter history of monetary stability. We provide evidence that the same conditions identified in the literature which enable forecasting models to work in advanced economies (purchasing power parity adjustment through exchange rates rather than relative prices, credible inflation targeting regimes, etc.) also hold in EMs.

This paper is structured as follows. Section 2 provides background for the reader, detailing the challenges identified in the literature when forecasting exchange rates, as well as a brief exposition on the way nominal exchange rates in EMs adjust to close relative exchange rate gaps. Section 3 details the methodology, comparing the SCHL model to alternative forecasting methods. Section 4 presents the results: we show the SCHL's performance against competing methods and provide a simple rule of thumb for forecasting EM exchange rates over the medium term. Section 5 concludes.

2 Background: exchange rate forecasting in Emerging Markets

2.1 Advances in the literature

For decades, exchange rate forecasting models were unable to beat a random walk process. The problem was initially noted in Meese and Rogoff (1983), comparing the random walk against structural models based on interest and inflation differentials, and was corroborated by further research over the years: productivity-based and behavioral equilibrium models, sticky price monetary models and time-varying parameters all failed at overcoming the problem (Bacchetta et al., 2010; Alquist and Chinn, 2008; Cheung et al., 2005).

And yet a growing literature, particularly in the 21st century, has produced evidence to the contrary. Clark and West (2006) shows that an interest parity model can outperform the random walk once the test statistic is adjusted to correct for small-sample bias,[1] while Molodtsova and Papell (2009) finds significant predictive capabilities in a Taylor rule-based model. More generally, Rossi (2013) conducts a review of the available literature and finds that some approaches, particularly monetary policy rules and single-equation error correction models, may outperform the random walk some of the time, depending on the forecast horizon, sample period, and chosen predictor.

The improved performance of exchange rate models in recent years appears is tied to the substantial progress made by monetary policy over the past two decades. Inflation targeting, in particular, has provided a transparent and explicit focus on price stability, anchoring inflation expectations and reducing uncertainty for market participants. Stabilizing inflation means stabilizing interest rate differentials, which are key determinants of exchange rate movements, and this, in turn, has led to better performance for forecasting models. Improvements in central bank credibility and independence further bolstered this trend. Another key element has been the widespread adoption of floating exchange rates, which respond more directly to fundamentals and are associated with more rapid reversals to the mean in real exchange rates (Engel and Wu, 2024; Ca'Zorzi et al., 2021; Eichenbaum et al., 2017).

Against this backdrop, a specific strand of the literature has proposed forecasting models based on purchasing power parity (PPP): if real exchange rates are more or less constant over time, then movements in nominal exchange rates are determined by the inflation differential between a given pair of countries. There are strong indications that PPP can hold over long-term horizons, even as it fails to hold over the short run (Bahmani-Oskooee and Hegerty, 2009; Engel, 2000; Taylor and Taylor, 2004; Froot and Rogoff, 1995), and, because they do not rely on data filtering or cointegrating parameters, PPP-based exchange rate

[1] Although Alquist and Chinn (2008) fails to find support for the predictive power of a number of forecasting models even after using this alternative procedure.

models are less likely to suffer from many of the out-of-sample issues that undermine other forecasting methods (Rossi, 2013).

An especially promising PPP-based approach, proposed in Zorzi and Rubaszek (2020), is the half-life model (HL), where real exchange rate deviations from the historical mean are assumed to adjust entirely through the nominal exchange rate at a geometric rate. The HL model, calibrated for advanced economies according to the evidence in Rogoff (1996), has been shown to reliably outperform the random walk.

The development in the literature discussed so far have, by and large, focused on advanced economies. Forecasting exchange rates in EMs poses unique challenges due to more volatile macroeconomic environments, historically higher inflation differentials, greater exposure to external shocks, and varying degrees of capital controls. Early research documented frequent breaks in exchange rate relationships for EMs, linking them to sudden stops of capital inflows or abrupt policy change (Calvo et al., 2004). In this context, standard structural models—like uncovered interest parity or monetary fundamentals—often struggled to outperform naive forecasts. Nevertheless, more recent studies suggest that structural improvements in macroeconomic policy and increasing financial integration have enhanced the performance of certain forecasting models, particularly for EMs that have adopted more transparent and rules-based frameworks for exchange rate policy (Mishkin and Schmidt-Hebbel, 2007).

A critical dimension in these structural improvements has been the liberalization of capital accounts. Pasricha et al. (2018) find that EMs with greater de jure financial openness experience more predictable exchange rate behavior, consistent with the international trilemma, as lower barriers to cross-border transactions facilitate rapid adjustments in currency markets and help align nominal exchange rates with underlying fundamentals (Fratzscher, 2012). As EMs have progressively opened their capital accounts and become better integrated to global financial markets, the applicability of standard macroeconomic models for exchange rate forecasting has increased in tandem.

Equally important is the ongoing shift toward inflation-targeting regimes and enhanced central bank independence in emerging markets.Transparent and credible inflation targeting can anchor expectations, thereby reducing exchange rate volatility and lending more stability to nominal and real exchange rate relationships (Gonçalves and Salles, 2008). With inflation expectations more firmly tethered, EM interest rate differentials become a more reliable signal, enhancing the utility of policy-based or Taylor-rule-style forecasting models.

Finally, machine learning and big-data frameworks are increasingly used to parse out these global factors from domestic ones, refining forecasts by identifying nonlinearities that simpler econometric models may miss (Dautel et al., 2020). Taken together, the development of greater capital account openness, more credible monetary frameworks, and better data-driven techniques have gradually improved exchange rate forecasting in EMs.

In the rest of this chapter, we show that the HL model would be an appropriate fit for EMs: we examine the validity of long-run PPP for our sample of chosen countries, and present evidence that nominal exchange rates, rather than relative prices, do the bulk of the adjustment in restoring purchasing power parity. Having established the validity of the HL model for our set of chosen EMs, the following chapters construct exchange rate forecasts and show that the HL model outperforms both the random walk and a number of alternative specifications.

2.2 Nominal exchange rates, not relative prices, restore PPP

PPP by itself is not sufficient to predict changes in a country's currency. Whenever the real exchange rate deviates from its long-run value, the necessary adjustment could come either from a movement in the nominal exchange rate or from a shift in relative prices. Only if the currency is doing most of the adjustment would PPP be an effective basis for a forecasting model.

In order to analyze the dynamics of the real exchange rate and their relationship with the nominal exchange rate and the relative prices, we estimate the following regressions:

$$\Delta rer_{t,h} = \alpha_{0h} + \alpha_{1h} rer_{t-h} + \varepsilon_t$$
$$\Delta ner_{t,h} = \beta_{0h} + \beta_{1h} \Delta rer_{t,h} + \varepsilon_t$$
$$\Delta rpi_{t,h} = \gamma_{0h} + \gamma_{1h} \Delta rer_{t,h} + \varepsilon_t$$

Where $\Delta rer_{t,h}$ represents $\Delta rer_{t,h} = rer_t - rer_{t-h}$, the same applies for the rest of the variables.

If the real exchange rate exhibits mean reversion, implying that PPP holds, then α_{1h} is expected to approach -1 with an increase in horizon h. Moreover, if the real exchange rate's adjustment is primarily driven by changes in the nominal exchange rate rather than shifts in relative prices, then we should observe $\beta_{1h} = 1$ and $\gamma_{1h} = 0$. As shown in Table 1, this pattern is observed across nearly all currencies at all horizons.

Table 1: Exchange rate dynamics

Country	6 months			2 years			3 years		
	Estimates of $\Delta rer_{t,h} = \alpha_{0h} + \alpha_{1h} rer_{t-h} + \varepsilon_t$								
	α_{0h}	α_{1h}	R^2	α_{0h}	α_{1h}	R^2	α_{0h}	α_{1h}	R^2
Brazil	-0.1	-0.1	0.05	-0.34	-0.36	0.17	-0.55	-0.59	0.31
Chile	-0.96	-0.15	0.07	-2.8	-0.44	0.19	-4.41	-0.69	0.33
Colombia	-0.7	-0.09	0.04	-2.24	-0.28	0.11	-3.87	-0.49	0.21
Egypt	-0.28	-0.14	0.07	-1.2	-0.62	0.29	-1.7	-0.88	0.42
Hungary	-0.86	-0.16	0.1	-2.81	-0.51	0.35	-3.66	-0.67	0.45
India	-0.33	-0.08	0.06	-1.27	-0.33	0.27	-1.62	-0.42	0.43
Indonesia	-1.12	-0.12	0.07	-5.16	-0.56	0.46	-6.37	-0.69	0.57
Mexico	-0.34	-0.13	0.07	-0.93	-0.35	0.19	-1.16	-0.43	0.23
Peru	-0.09	-0.08	0.05	-0.37	-0.33	0.19	-0.58	-0.52	0.29
Poland	-0.26	-0.21	0.12	-0.6	-0.49	0.27	-0.7	-0.57	0.32
South Africa	-0.35	-0.15	0.06	-1.39	-0.61	0.26	-1.64	-0.73	0.34
Thailand	-0.26	-0.07	0.03	-1.3	-0.37	0.24	-1.97	-0.56	0.39
Turkey	-0.03	-0.03	0.01	-0.08	-0.06	0.01	-0.17	-0.17	0.03
	Estimates of $\Delta ner_{t,h} = \beta_{0h} + \beta_{1h} \Delta rer_{t,h} + \varepsilon_t$								
	β_{0h}	β_{1h}	R^2	β_{0h}	β_{1h}	R^2	β_{0h}	β_{1h}	R^2
Brazil	-0.02	1.02	0.98	-0.07	1.06	0.97	-0.11	1.05	0.96
Chile	-0.01	1.06	0.97	-0.02	1.11	0.97	-0.03	1.11	0.98
Colombia	-0.01	1.02	0.97	-0.05	1.04	0.97	-0.07	1.03	0.97
Egypt	-0.04	1.06	0.9	-0.15	1.08	0.87	-0.23	1.05	0.86
Hungary	-0.01	0.96	0.95	-0.04	0.91	0.93	-0.05	0.87	0.94
India	-0.02	0.9	0.78	-0.07	0.82	0.64	-0.1	0.77	0.48
Indonesia	-0.02	0.95	0.89	-0.06	0.81	0.79	-0.09	0.75	0.72
Mexico	-0.01	1.03	0.94	-0.04	1.06	0.98	-0.05	1.09	0.98
Peru	-0.0	1.0	0.9	-0.01	1.02	0.91	-0.02	1.06	0.92
Poland	-0.0	1.02	0.97	-0.01	1.02	0.94	-0.01	1.02	0.93
South Africa	-0.01	1.01	0.98	-0.05	1.04	0.96	-0.08	1.06	0.95
Thailand	0.0	0.92	0.96	0.01	0.85	0.95	0.02	0.8	0.93
Turkey	-0.07	1.07	0.73	-0.24	1.16	0.52	-0.33	1.12	0.57
	Estimates of $\Delta rpi_{t,h} = \gamma_{0h} + \gamma_{1h} \Delta rer_{t,h} + \varepsilon_t$								
	γ_{0h}	γ_{1h}	R^2	γ_{0h}	γ_{1h}	R^2	γ_{0h}	γ_{1h}	R^2
Brazil	0.02	-0.02	0.01	0.07	-0.06	0.08	0.11	-0.05	0.07
Chile	0.01	-0.06	0.09	0.02	-0.11	0.27	0.03	-0.11	0.28
Colombia	0.01	-0.02	0.01	0.05	-0.04	0.05	0.07	-0.03	0.02
Egypt	0.04	-0.06	0.03	0.15	-0.08	0.04	0.23	-0.05	0.02
Hungary	0.01	0.04	0.03	0.04	0.09	0.12	0.05	0.13	0.26
India	0.02	0.1	0.04	0.07	0.18	0.08	0.1	0.23	0.08
Indonesia	0.02	0.05	0.02	0.06	0.19	0.16	0.09	0.25	0.23
Mexico	0.01	-0.03	0.02	0.04	-0.06	0.13	0.05	-0.09	0.22
Peru	0.0	-0.0	0.0	0.01	-0.02	0.0	0.02	-0.06	0.03
Poland	0.0	-0.02	0.01	0.01	-0.02	0.01	0.01	-0.02	0.01
South Africa	0.01	-0.01	0.0	0.05	-0.04	0.04	0.08	-0.06	0.05
Thailand	-0.0	0.08	0.15	-0.01	0.15	0.37	-0.02	0.2	0.46
Turkey	0.07	-0.07	0.01	0.24	-0.16	0.02	0.33	-0.12	0.01

3 Methodology

3.1 Forecasting Models

We introduce the Self-Calibrated Half Life (SCHL) model for exchange rate forecasting, a modified version of the half-life (HL) model in Zorzi and Rubaszek (2020), leveraging Machine Learning to optimize the model's mean-reverting parameter. As we will show below, the SCHL outperforms alternative methods when applied to an Emerging Markets context: we compare a random walk (RW), an autoregressive process (AR), a half life model (HL), a direct forecast model (DF), and a panel direct forecast model (PDF) against our proposed SCHL approach. With the exception of the RW, all other contenders are mean-reverting. In contrast, the RW assumes that purchasing power parity does not hold.

To compare the performance of the different models methods, we compute the ratio of each method's root mean square forecast error statistic (RMSE) to that of the RW. If the ratio is less than one, the model outperforms the random walk.

The predictions from each model are produced using a rolling regression with a minimum window of 120 months, or 10 years.[2] If, for example, the sample begins in 2000:1 the model forecast would begin in 2010:1, using 2000:1 to 2009:12 as a training dataset. The goal is to obtain exchange rate forecasts at horizons of one, six, twenty-four and thirty-six months.

With this methodology, every model will have 168 one-month-ahead forecasts, 167 two-month-ahead-forecasts, etc. That is, using a 120-month window (2000:1 to 2009:12), the first one-month-ahead forecast corresponds to 2010:1, but the first two-month-ahead forecast corresponds to 2010:2. Therefore, longer horizons will have smaller total forecasts.

3.1.1 Random Walk Model

The RW is the baseline model against which we compare all other contenders, and is given by:

$$q_{t+h} = q_{t-1} + \epsilon_t \tag{1}$$

Where q is the log of the real exchange rate. In the random walk model, the best prediction for the real

[2] This window is chosen so as to rely on a dataset with sufficient time to obtain relevant PPP measures, but it's worth pointing out that successive rounds of regressions use windows that are larger than 120 months. For the first round of predictions, We rely on data from 2000:1 to 2009:12, then generate forecasts for the various time horizons. In the next round, We generate forecasts using data from 2000:1 to 2010:1, so the regression has a larger sample as time goes on.

exchange rate at any time $t+h$ is the real exchange rate's current value at time t. As an example, consider a RW forecast based on training data from 2000:1 to 2009:12. The best prediction for the real exchange rate either one, two, or even twelve months ahead is always the same: the real exchange rate in 2009:12. After advancing one period, the RW-based forecast for any time horizon becomes the real exchange rate in 2010:1.

3.1.2 AR(1)

The first contender against which we compare the RW is an autoregressive model of order one. Specifically:

$$q_t = \mu + \rho \cdot (q_{t-1} - \mu) + \epsilon_t \tag{2}$$

Note that the sample mean, μ, is a moving average. The mean used in the regression for forecasting the one-month ahead real exchange rate in 2010:1 will be the average of the real exchange rate from 2000:1 to 2009:12. When forecasting the one-month ahead level for 2010:2, though, the new sample mean will cover 2000:1 to 2010:1.

Note also that when predicting the real exchange rate for a longer time horizon (say, six months) the model must first create estimates for the intervening months between t and $t+h$, and use them as an input for the $t+h$ prediction.

3.1.3 Half Life Model

The unifying theme behind all the models being compared is that they all revert back to the mean, which is given by purchasing power parity. The equations for the HL model are the same as in the AR(1) model, except that one imposes a reversion to the mean in the real exchange rate that is gradual and linear. Specifically, parameters are calibrated such that this adjustment to the mean is completed in 36 months, or 3 years. The selection of the pace of convergence is made considering the results in Zorzi and Rubaszek (2020), which finds that a half life model calibrated with a reversion to the mean of 36 months, as in Rogoff (1996), tends to outperform the random walk model in Advanced Economies.

3.1.4 Direct Forecast Model

The next two models are called direct forecast models because We estimate the conditional expectation of the pace of adjustment on the real exchange rate directly and independently for each horizon. The main difference with the iterated forecast models is that if We forecast to a horizon say of 6 months we directly

estimate that coefficient independently of the forecast of 1 month ahead, in the iterated forecast models, as the AR(1), We would estimate the intermediate coefficient and used them as an input to reach the 6 months ahead forecast.

In the DF model, the following regression is run for each country separately:

$$\Delta q_{t,h} = \alpha_{0,h} + \alpha_{1,h} \cdot (q_{t-h} - \mu) + \epsilon_t \tag{3}$$

Where $\Delta q_{t,h} = q_t - q_{t-h}$. The term in parentheses in the right-hand side is the gap between the real exchange rate and PPP at time t, which in turn is given by the sample moving average.

This approach will yield an estimate for $\alpha_{0,h}$ and $\alpha_{1,h}$ for each country. The forecast is then computed as:

$$E_t [q_{t+h}] = q_t + \alpha_{0,h} + \alpha_{1,h} \cdot (q_t - \mu) \tag{4}$$

As an example for clarifying how this method works, consider the first one month ahead forecast, We use as a train data set from 2001:1 to 2009:12, 120 months, so when we generate variable $\Delta q_{t,h}$ We have 119 observations. Our regression will consist on a sample of 119 observations, We run it and use the obtained coefficients to forecast on 2010:01. If we expand the time horizon, say a six month ahead forecast, We work with the same train data set, of 120 months, but now We have fewer observations of $\Delta q_{t,h}$, specifically 114, which turns our regression sample to 114 observations. The rest of the forecast is equal.

3.1.5 Panel Direct Forecast Model

This approach follows the same structure as the DF model, but $\alpha_{0,h}$ and $\alpha_{1,h}$ are estimated for the entire panel using fixed effects. Then, forecasts are produced for each country using the coefficients obtained from the entire panel.

3.1.6 Self-Calibrated Half Life Model

Our proposed approach is a self-calibrated version of the half-life model. The baseline HL approach uses a pace of convergence of 36 months, calibrated to evidence from Advanced Economies, whereas our model will enhance the parameter calibration to achieve improved forecasting accuracy for Emerging Markets. Specifically, our SCHL model leverages machine learning techniques to derive an optimal mean-reversion parameter.

The forecasting models presented earlier use a training set spanning from 2000:01 to 2009:12, and a testing set from 2010:01 to 2023:12. Since they do not rely on this training data for testing, we capitalize on this period to fine-tune the parameter without compromising the validity of the cross-model comparison. The SCHL model, specifically, is trained on data from 2000:01 to 2004:12, with a testing period from 2005:01 to 2009:12. As successive rounds of predictions are made, the sample size gradually increases.

The HL model is based on a predefined number of months that dictate the pace of convergence to the PPP exchange rate. Since (Rogoff, 1996) implies that the pace of reversion is between three and five years, we extend the applicability of this assumption, broadening the convergence horizon to a range from two to six years, or 24 to 72 months. The SCHL model recalibrates the pace of convergence for each month within this range. After running model for different forecast horizons from the one-month-ahead to the thirty-six-month-ahead forecast, we calculate the median of each country's RMSE for each month of convergence and forecast horizon pair.[3] This allows us to identify which convergence month yields the lowest RMSE for each forecast horizon. Finally, we group the forecast horizons into short term (1 to 6 months) medium term (7 to 18 months), and long term (19 to 36 months) groups, and pick out the average optimal convergence month.

One potential concern that may arise is that, given that Emerging Markets have only featured floating exchange rates and monetary stability for a few decades, the sample size for our model may be too limited. There are several important points worth noting in this regard. First, our objective is not to draw causal inference conclusions, but rather to achieve better predictive performance compared to competing models. Our focus is therefore on identifying a model that performs well in out-of-sample predictions, where "out-of-sample" refers to the original division of the data into training and testing sets (this is where machine learning intuition comes in). Second, one must keep in mind that an HL model does not involve estimating parameters; instead, they are imposed, by selecting the parameter that minimizes the RMSE. As such, the potential issue of an insufficiently large sample for generating consistent parameter estimates is not relevant to our model.

It is worth highlighting that our sample is used in two separate ways. One, the SCHL model generates forecasts based on rer^{ppp}, which we calculate as the rolling mean of the rer. A larger training set does improve the accuracy of this variable, but using 60 months appears to provide a sufficiently consistent calculation for the first observation (in addition, with each successive round one month is added to the sample). Two, while comparing the RMSE across different forecast horizons, the one-month-ahead forecast includes 60 observations per country, whereas subsequent horizons have slightly fewer observations. Since our dataset comprises 13 countries, we do not anticipate this to significantly affect our estimates. But our main argument is that if the sample size were indeed too small, this would be reflected in the out-of-sample

[3]Since we aim a model with an accurate performance out of sample, We take the median of the countries RMSE in order to mitigate the impact of potential outliers that could introduce noise into the calculations.

performance of our SCHL model compared to alternative models.

3.2 Data

Our dataset, collected from the IMF-IFS database, includes the monthly end-of-period nominal exchange rate against the USD (NER) and the consumer price index (CPI) data over the period 2000:1-2023:12 for the following set of countries: Brazil (BRA), Chile (CHL), Colombia (COL), Egypt (EGY), Hungary (HUN), India (IND), Indonesia (IDN), Mexico (MEX), Peru (PER), Poland (POL), South Africa (ZAF), Thailand (THA), and Turkey (TUR).[4] Our sample of emerging countries is composed of countries that have data for the entire detailed period and which are characterized by not having a fixed nominal exchange rate.[5] With this dataset we have constructed the bilateral real exchange rate as:

$$rer_t = ner_t + rpi_t \tag{5}$$

The variable $rpi = p - p^*$ represents the relative price index (domestic vs. U.S.), while ner denotes the nominal exchange rate (USD per unit of domestic currency), with all variables expressed in logarithms. According to this definition, an increase in both the real and nominal exchange rates reflects an appreciation of the domestic currency against the USD.

4 Results

4.1 Performance against other forecasting methods

As previously mentioned, the first step was to compare the forecast accuracy at different horizons for a random walk (RW), an autoregressive process (AR), a half life model (HL), a direct forecast model (DF), and a panel direct forecast model (PDF). The results of this forecast comparison are presented in Table 2. First, the AR model underperforms relative to the RW across all horizons. Second, while the DF model occasionally performs well, it generally tends to perform worse than the RW, which also holds for the PDF model. Although the PDF model outperforms the DF, it is still notably less accurate than the RW . When comparing direct forecasting to iterative forecasting, the former tends to be more accurate. However, the main finding is that the HL model, with a convergence period of 36 months, tends to outperform the RW, specially at the forecast horizon increases.

[4]The inclusion of United States is to construct the bilateral real exchange rate.

[5]Specifically, EMs with either managed or freely floating currencies according to Ilzetzki et al. (2019).

Table 2: RMSE for the RER with respect to the RW

	1 month				6 months			
	AR(1)	DF	PDF	HL(36)	AR(1)	DF	PDF	HL(36)
BRA	1.00	1.00	1.00	1.00	1.03	1.00	1.00	0.99
CHL	1.00	1.00	1.00	1.00	1.01	1.01	0.99	0.99
COL	1.00	1.00	1.00	1.00	1.02	1.02	1.01	1.00
EGY	1.00	1.00	0.99	0.99	1.00	0.98	0.97	0.97
HUN	1.01	1.00	1.00	0.99	1.05	1.01	1.01	0.96
IND	1.01	1.01	1.00	1.00	1.05	1.04	1.00	1.02
IDN	1.01	1.00	1.00	1.00	1.06	1.03	1.02	1.00
MEX	1.00	1.01	1.00	1.00	1.00	1.12	1.00	1.00
PER	1.00	1.00	1.00	1.00	1.03	1.03	1.00	1.01
POL	1.01	1.00	1.00	0.99	1.04	1.00	1.00	0.96
ZAF	1.00	1.00	1.00	1.00	1.01	1.07	1.01	1.01
THA	1.00	1.00	1.00	1.00	1.02	1.01	1.01	1.01
TUR	1.01	1.01	1.01	1.01	1.05	1.08	1.12	1.11
	2 years				3 years			
BRA	1.14	1.07	1.02	0.90	1.20	1.17	1.12	0.86
CHL	1.05	1.09	1.05	0.96	1.09	1.13	1.08	0.89
COL	1.13	1.20	1.11	0.99	1.21	1.33	1.14	0.91
EGY	1.02	0.98	0.86	0.87	1.03	1.13	0.79	0.80
HUN	1.37	1.34	1.33	0.93	1.56	1.50	1.49	0.90
IND	1.39	1.31	0.85	1.03	1.70	2.09	0.90	1.26
IDN	1.36	1.14	1.12	0.80	1.51	1.26	1.06	0.63
MEX	1.00	1.27	1.03	1.05	1.00	1.11	1.04	1.07
PER	1.14	1.30	1.01	0.96	1.26	1.84	1.00	0.88
POL	1.27	1.12	1.11	0.90	1.46	1.37	1.30	0.90
ZAF	1.05	1.31	1.11	0.99	1.10	1.52	1.30	0.99
THA	1.12	1.12	0.97	0.94	1.18	1.24	0.90	0.86
TUR	1.21	1.50	1.58	1.32	1.26	1.62	1.60	1.25

The next step involves comparing the performance of the SCHL model with the baseline 36-month HL model. As outlined in the methodology section, the process identifies the optimal convergence month for each forecast horizon-short, medium and long term-while the overall calibrated parameter is determined by averaging across periods. Table 3 shows the optimal convergence period for each term and the final calibrated convergence period.

Table 3: Optimal SCHL convergence month by horizon

Mean	Short Term	Medium Term	Long Term
61	72	38	72

These results highlight the critical role of parameter calibration in the HL model. In the short run, the model indicates that a convergence horizon of 72 months yields the most accurate predictions. Interestingly, the same 72 month calibration proves optimal in the long run, indicating persistent deviations of the RER over extended periods. In contrast, the medium term horizon shows that a shorter convergence period of 38 months provides better predictive accuracy.

To understand these results requires a closer examination of the calibrated parameter's role in the HL model. The variation in optimal calibration across different time horizons sheds light on the real exchange rate adjustment process. Our estimation suggest that emerging countries tend to have highly persistent deviations from the PPP real exchange rate values in the short and long term while this persistence tends to lower in the medium term.

When the persistence is higher, the model is more driven by the last rer ppp observation i.e. the RW can make a good job forecasting the exchange rate. This is probably because emerging markets are very noisy in the short run. But, there is a big persistence in the long run also, for the same reason, forecast long horizons in emerging markets that has a lot of external and internal shocks is a heavy duty. But, what we discover is that the persistence is lower in the medium term where appears an interesting opportunity to forecast.

The primary goal of this section is to compare the baseline 36-month HL model, which has proven to be the most effective predictive model for the real exchange rate, with our SCHL model, which optimally converges at 61 months. The forecast comparison results are presented in Table 4. In nearly every forecast horizon, the SCHL model consistently outperforms the baseline HL model.

Table 4: RMSFE for the RER with respect to the RW.

	1 month		6 months		1 year		3 years	
	HL(36)	HL(61)	HL(36)	HL(61)	HL(36)	HL(61)	HL(36)	HL(61)
BRA	1.00	1.00	0.99	0.98	0.97	0.96	0.86	0.87
CHL	1.00	1.00	0.99	0.99	0.98	0.97	0.89	0.90
COL	1.00	1.00	1.00	0.99	1.01	0.99	0.91	0.91
EGY	0.99	1.00	0.97	0.98	0.94	0.95	0.80	0.85
HUN	0.99	0.99	0.96	0.97	0.93	0.95	0.90	0.90
IND	1.00	1.00	1.02	0.99	1.02	0.97	1.26	0.97
IDN	1.00	1.00	1.00	0.99	0.97	0.95	0.63	0.69
MEX	1.00	1.00	1.00	0.99	1.00	0.99	1.07	1.01
PER	1.00	1.00	1.01	0.99	1.01	0.98	0.88	0.87
POL	0.99	0.99	0.96	0.97	0.93	0.95	0.90	0.90
ZAF	1.00	1.00	1.01	1.00	1.02	1.00	0.99	0.97
THA	1.00	1.00	1.01	1.00	1.02	0.98	0.86	0.86
TUR	1.01	1.00	1.11	1.05	1.22	1.11	1.25	1.15

The key intuition of a half-life model is that real exchange rate deviations tend to be corrected through nominal exchange rates rather than relative prices. The question is the speed with which this happens (that is, the correct value of the mean-reversion parameter). Our results, shown in Table 5 below, indicate that both the SCHL and the HL overperform the RW when aplied to Emerging Marekts, over all forecast horizons. The HL(36) model performs better for some countries also performs worse for others, but the HL(61) tends to be more conservative in its forecasts, hence our preferred model is the HL(61).

Table 5: RMSFE for the NER with respect to the RW.

	1 month		6 months		1 year		3 years	
	HL(36)	HL(61)	HL(36)	HL(61)	HL(36)	HL(61)	HL(36)	HL(61)
BRA	1.00	1.00	0.98	0.98	0.88	0.90	0.84	0.88
CHL	1.00	1.00	1.00	0.99	0.96	0.96	0.89	0.91
COL	1.00	1.00	1.02	1.00	0.98	0.97	0.90	0.92
EGY	0.99	1.00	0.97	0.98	0.88	0.92	0.84	0.89
HUN	1.00	1.00	0.99	0.99	0.98	0.97	0.98	0.97
IND	0.98	0.99	0.88	0.92	0.56	0.70	0.49	0.65
IDN	0.99	0.99	0.94	0.95	0.70	0.79	0.60	0.72
MEX	1.00	1.00	1.03	1.01	1.12	1.05	1.13	1.07
PER	1.00	1.00	0.98	0.98	0.87	0.89	0.75	0.81
POL	0.99	1.00	0.98	0.98	0.95	0.95	0.99	0.96
ZAF	1.00	1.00	1.02	1.01	1.01	0.99	1.01	0.99
THA	1.00	1.00	1.02	1.00	0.99	0.94	0.94	0.89
TUR	1.05	1.03	1.14	1.08	1.15	1.10	1.12	1.08

4.2 Forecasting nominal exchange rates

A great benefit of half-life models is their simplicity in forecasting nominal exchange rates: it can be done in minutes and with little algebraic skill. All the user needs to do is estimate the real exchange rate's 'misalignment' by comparing its current value to the historical mean. Since PPP adjustments take place through nominal exchange rates, this means that forecasting the level of the currency h months into the future is as simple as:

$$\Delta ner_{t+h,h} = (\rho^h - 1)(rer_t - \overline{rer}), \tag{6}$$

With rer_t being the current levle of the real exchange rate, and $\overline{rer}$ the historical mean. Note that ρ is the monthly persistence parameter of the SCHL model, which, as per our previous results, corresponds to a half-life of approximately 61 months (e.g. $\rho \approx 0.989$, for monthly data).

The SCHL model therefore predicts that nominal exchange rates in EMs adjust to correct real exchange rate misalignments as follows: one-tenth of the required adjustment is achieved in the first 10 months, one-fifth in 20 months, and one-quarter in 24 months. In other words the nominal exchange rate adjustment over the next 10 months can be approximated by multiplying the real exchange rate misalignment by −0.10.

Figures 1 and 2, below, show the exchange rate forecasts for our entire sample produced by 36 month-ahead SCHL and RW models, compared to the actual observed values at any given date. The self-calibrated half life approach outperforms the random walk for most countries, particularly for those where currencies are allowed to float and monetary authorities pursue inflation targets.

Figure 1: EM Exchange Rate Forecasts

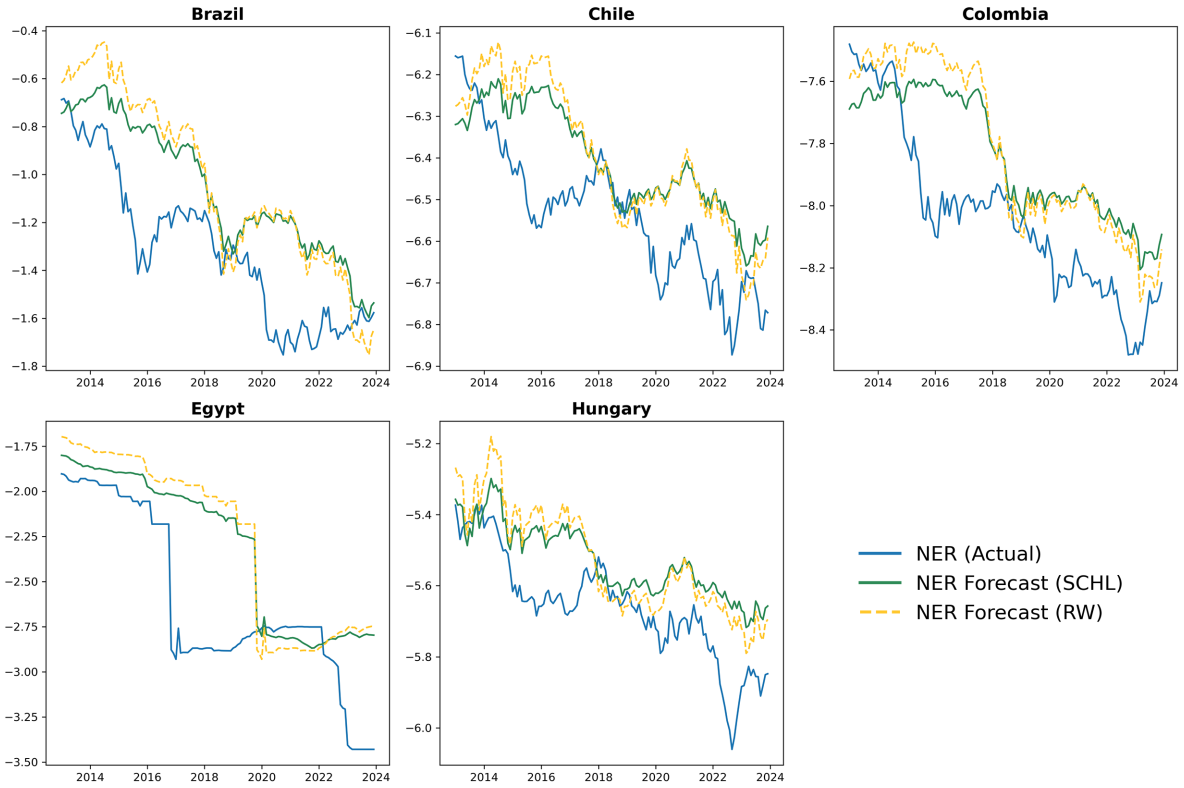
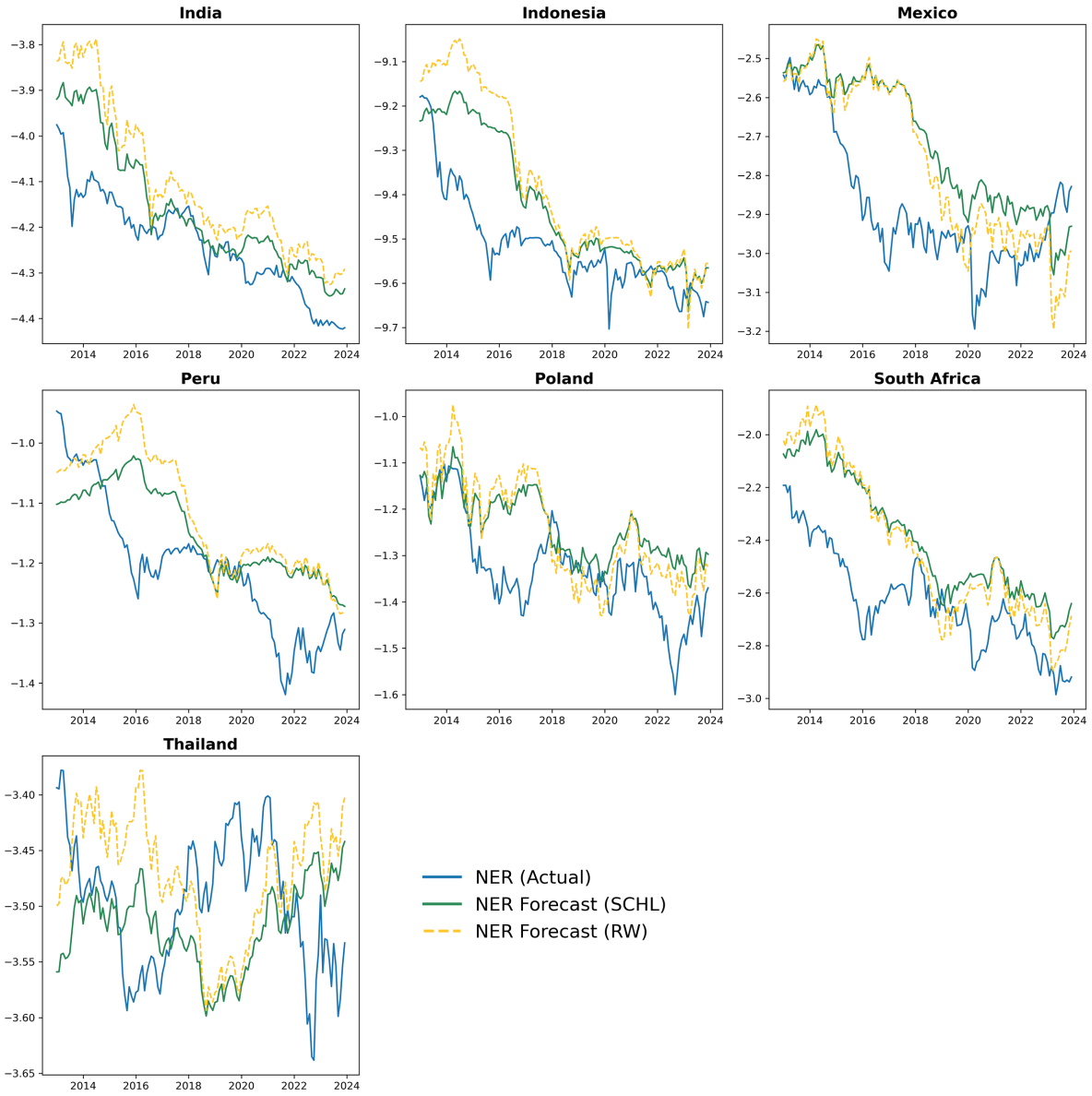


Figure 2: EM Exchange Rate Forecasts (continued)



5 Conclusion

The findings in this paper contribute to the ongoing evolution of exchange rate forecasting by demonstrating that emerging markets exhibit systematic exchange rate adjustment dynamics similar to those observed in advanced economies. By developing the Self-Calibrating Half-Life (SCHL) model, we show that machine learning techniques can be effectively used to optimize forecasting parameters, leading to improved predictive accuracy relative to traditional models. This represents an important step toward

bridging the gap between empirical forecasting methods and economic theory, particularly in the context of purchasing power parity (PPP) reversion.

Our results challenge the long-standing notion that exchange rates in EMs are inherently more difficult to predict than those in advanced economies. While structural differences remain—such as greater exposure to external shocks and capital flow volatility—the underlying mechanism of exchange rate adjustment appears to operate in a similar fashion. This suggests that as EMs adopt more credible monetary frameworks and open their capital accounts, the effectiveness of fundamentals-based forecasting models will continue to improve.

While the SCHL model offers a significant methodological innovation, it also raises several important questions for future research. First, given the demonstrated importance of inflation targeting in enhancing exchange rate predictability, further analysis is needed to determine how different monetary policy frameworks influence half-life dynamics. Second, while our model performs well across a range of EMs, variations in the estimated half-life parameter imply that country-specific factors play a role in determining the speed of adjustment.

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