



Boosting Carry with Equilibrium Exchange Rate Estimates

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Abstract

We construct currency portfolios based on the premise that exchange rates gradually converge toward their equilibrium levels, yielding three key findings. First, this convergence can be leveraged to build profitable portfolios. Second, the slow rate of convergence over shorter horizons aligns with the sustained profitability of carry trade strategies, where investors borrow in low-yield currencies and invest in high-yield ones. Third, incorporating the predictive insights of equilibrium exchange rates can boost the performance of carry trade strategies.

Keywords Equilibrium exchange rate · Carry trade · Trading strategies

JEL Classification F31 · G12 · G15

1 Introduction

Since the pioneering work of Meese and Rogoff (1983) a widespread skepticism has prevailed about the usefulness of economic models to predict exchange rates, given that they often generate larger forecast errors than the random walk benchmark. This view still dominates the profession, as confirmed by the comprehensive survey papers of Rossi (2013) and Cheung et al. (2019). One important qualification to this consensus view comes from a new strand of the exchange rate literature, arguing that a good forecasting strategy consists in assuming a gradual return of exchange rates to their long run equilibria. Knowing the terminal point of the real exchange rate, which could be proxied by the relative purchasing power parity (*PPP*), is often enough to outperform the random walk in real but also nominal exchange rate forecasting, since

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the adjustment takes place mostly via currency and not relative price movements (Mark and Sul 2012; Ca' Zorzi et al. 2017; Ca' Zorzi and Rubaszek 2020; Ca' Zorzi et al. 2022; Engel and Wu 2023). An interesting aspect from this paper's perspective is that the process of exchange rate convergence to equilibrium is already visible at the one quarter horizon, even if the adjustment process proceeds initially "at snail's pace", before gathering momentum at medium-term horizons (Ca' Zorzi et al. 2022).

Taking these findings of the (time series) exchange rate predictability literature at face value poses three captivating questions from a currency investor perspective. First, is it possible to exploit the above predictive power of equilibrium exchange rate models to build an FX trading strategy with desirable return and risk properties? Second, how the performance of such a strategy compares to that of existing benchmark FX portfolios, which exploit the cross-sectional predictability of currency returns? And third, can equilibrium exchange rate models help boost the performance of a naïve carry trade strategy, consisting in borrowing in low-yield and investing in high-yield currencies, which presumes that exchange rates are unpredictable?

The aim of this paper is to address the above questions by developing a currency portfolio strategy, which exploits time series and delivers cross-sectional exchange rate predictability. To ensure predictive power, we employ two common equilibrium exchange rate measures, taken from the PPP and the Behavioral Equilibrium Exchange Rate (*BEER*) literature. For the adjustment process, we assume that the exchange rate converges to its equilibrium gradually, completing half of the adjustment in either three or ten years. To assess cross-sectional predictability, we turn to the vast currency portfolio literature and the most popular FX strategy in that literature, i.e. carry trade. One fundamental aspect of this strategy is that it takes advantage of the prevailing interest rate configuration while remaining completely agnostic about future exchange rate movements. In this sense, it is fully compatible with the random walk hypothesis.

The currency trading literature has investigated the role of economic fundamentals both to rationalize profits from carry or to enhance them further. The study of Lustig et al. (2011) argues that by investing in high and borrowing in low interest rate currencies, FX investors earn profits but load on global risk. Several other studies investigate possible explanations for the past exceptional performance of carry portfolios (see Koijen et al. 2018, for a comprehensive discussion). Menkhoff et al. (2012a) find that excess returns of high interest rate currencies fall with the rise of global FX volatility, which implies that returns are negatively skewed. Following a similar insight, Jorda and Taylor (2012) show how gains from a naïve carry trade strategy would have been almost wiped out by the Great Financial Crisis and instead would have been sustained with a strategy adjusted for the role of exchange rate misalignments. In a similar context, the work by Anatolyev et al. (2017) shows that returns of carry strategy can be improved by capturing the tail of the distribution of excess returns, based on a decomposition into multiplicative sign and absolute return components. In turn, Barroso and Santa-Clara (2015) suggest that a combination of carry with two other common FX strategies, momentum and value, would have guaranteed extra profits for a given level of risk. Another variant of the carry strategy with enhanced risk-adjusted returns is proposed by Bekaert and Panayotov (2020), who suggest dropping currencies that systematically underperform from the FX portfolio.

While carry trade strategies receive most of the attention, the FX trading literature also focuses on two alternative strategies for extracting excessive returns from a currency portfolio, known as “currency value” and “momentum”. The notion of currency value is indeed akin to the concept of equilibrium exchange rate. It has been used before to account for the fair value of currencies in investment strategies, in general, and carry strategies specifically. In the application of Asness et al. (2013) currencies that are in real terms weaker than five years before are expected to rebound, hence generating excess returns. The time horizon of reference in this framework is much shorter than in the equilibrium exchange rate literature, as the latter typically requires twenty years of data for estimation purposes. In common with the equilibrium exchange rate literature, the analysis is often augmented with additional fundamentals. For instance, Menkhoff et al. (2017) adjust the benchmark measure of currency value for country-specific fundamentals, such as productivity, the quality of exported goods, net foreign assets, and output gaps. In a slightly different vein, Colacito et al. (2020) show, by constructing a well-performing FX portfolio, that the currency value can be revealed by regressing future currency returns and cross-country differences in the business cycle. Finally, the relationship between economic fundamentals and currency value is confirmed by Dahlquist and Hasseltoft (2020), who sort currencies on the basis of past trends in industrial production, retail sales, unemployment and inflation, showing that this approach exhibits attractive risk return characteristics.

Our analysis contributes to the above literature in the following major ways. First, we show the profitability of a foreign exchange portfolio strategy based on currency misalignments. While sharing with other papers the reliance on macroeconomic data to deliver cross-sectional FX predictability and develop a portfolio with competitive risk-return characteristics (Della Corte and Tsiakas 2012; Della Corte et al. 2016; Menkhoff et al. 2017; Dahlquist and Hasseltoft 2020; Colacito et al. 2020), our study is unique in exploiting the information content of US dollar misalignments to construct a transparent and easily explainable FX portfolio. Second, we illustrate how such strategy based on exchange rate misalignments underperforms relative to a carry strategy, because it ignores that the pace of exchange rate adjustments is slow. Gains that may be achieved by partly anticipating exchange rate movements at the one quarter horizons cannot outweigh those derived from knowing the prevailing configuration of interest rate differentials across the G10 countries. Third, we show that it is possible to build an effective strategy based on the predictable gradual convergence of exchange rates to their equilibria. We prove that this approach outperforms the carry strategy, if one postulates a sufficiently slow pace of exchange rate convergence. Models based on a slow rate of adjustment of exchange rates toward their equilibrium are competitive relative to carry strategies at half-lives of 2–3 years but their relative performance improves further and peaks at glacial rates of adjustment, i.e. for half-lives of 12 years for *PPP* and 7 years for *BEER*-based equilibrium exchange rate estimates. Fourth, we highlight how the proposed strategy can be described as an interpretable mix of carry and value strategies and therefore are directly relatable to those in the literature showing that a combination of carry with other strategies may offer higher returns than each of them in isolation (Della Corte and Tsiakas 2012; Asness et al. 2013; Menkhoff et al. 2017; Barroso and Santa-Clara 2015). Our proposed strategy profoundly changes the nature of the realized gains, as they become partly extracted by the predictability of

exchange rates with the *PPP* and *BEER* models and partly by the prevailing interest rate configuration.

The paper is structured as follows. In Section 2 we review the two most popular frameworks for calculating equilibrium exchange rates, i.e. the *PPP* and *BEER* models. In Section 3 we propose currency strategies based on equilibrium exchange rate estimates. In particular, we propose a currency strategy, labeled *half-life* (*HL*), which assumes that currency misalignments are halved in either three or ten years. In Section 4 we briefly reviewing our data sources. We present the main empirical results of our study in Section 5, which includes equilibrium exchange rate estimates and reviews their usefulness in predicting exchange rates and designing currency portfolios. Section 6 contains sensitivity analysis, where in particular we experiment the generality of our results for a broad range of half-lives. Finally, Section 7 draws the main conclusions of the paper.

2 Equilibrium Exchange Rate Concepts

Equilibrium exchange rate models are used to decompose the real exchange rate (Q) into its equilibrium value (Q^{eq}) and a misalignment component (Q^{mis}):

$$Q = Q^{eq} \times Q^{mis}$$

or in logarithmic notation:

$$q = q^{eq} + q^{mis},$$

where $q = \log(Q)$.

Such decomposition allows economists to judge whether currencies are over- or undervalued. Despite their limitations and the need to qualify the results judgmentally, these methods constitute an important building block of the quantitative toolbox used to support economic policy decisions at central banks and international organizations (Cubeddu et al. 2019; Coutinho et al. 2021). The key question, both from the perspective of policy-makers and investors, is how to derive the unobserved component q^{eq} and evaluate the reliability of such estimates.

In this section, we briefly review the two most popular methods for estimating equilibrium exchange rates for bilateral currency pairs, i.e. the *PPP* and *BEER* models.

Purchasing Power Parity The first equilibrium exchange rate model considered here is the *PPP* model, i.e. the oldest theory of real exchange rate determination, restored to prominence in modern times by Gustav Cassel and still today a key benchmark for determining exchange rate parities in fixed exchange rate regimes. In a nutshell, the *PPP* model starts from the law of one price, which states that international arbitrage helps to equalise the price of any tradable product denominated in a common currency. The concept of strong *PPP* emerges from applying this law to consumption baskets, i.e. the same basket of goods should cost the same across countries when denominated

in a common currency. In contrast, the weak version of *PPP* theory states that, in equilibrium, the relative cost of the same basket of goods across countries is constant, but might deviate from unity owing to factors such as taxes and/or transportation costs. The weak version of *PPP* is empirically more relevant and appealing, as it implies that a long-run sample mean of the real exchange rate, \bar{q} , is a good proxy for the *PPP*-based equilibrium real exchange rate, q^{PPP} :

$$q_{it}^{PPP} = \bar{q}_i, \quad (1)$$

where i denotes bilateral exchange rate against the US dollar and t is time index.

Behavioral Equilibrium Exchange Rate The implication of *PPP* theory is that real exchange rates should behave as mean-reverting stationary processes. However, many academics argue that the pace of mean reversion is, at best, surprisingly slow, pointing to the existence of a “*PPP* puzzle” (Rogoff 1996). The presence of this puzzle has encouraged several economists to search for plausible explanations that could justify the sluggishness of the adjustment process (Taylor et al. 2001). Other studies have instead taken a different route, challenging the assumption that real exchange rates are stationary and suggesting instead that their movements are linked to the evolution of other potentially non-stationary economic fundamentals. This methodology, which has been renamed several times in the literature, is most widely known either as the *BEER* model (MacDonald 1998) or, according to the IMF terminology, as the reduced-form model (Lee et al. 2008).

The literature has discussed at length the most plausible choice of fundamentals and the expected sign and magnitude of the parameters (see in particular Fidora et al. 2021). Our analysis includes three key fundamentals: relative per capita GDP (gdp), net foreign assets (nfa) and the terms of trade (tot).¹ As discussed in the literature, e.g. Ca’ Zorzi et al. (2022), a rise in each of these three variables should have a positive impact on the real exchange rate. In the case of gdp increase, the Balassa-Samuelson effect is a frequently cited explanation for real (equilibrium) exchange rate appreciation (Lee et al. 2013; Zhang 2017). A stronger nfa position or higher tot is also expected to lead to a real exchange rate appreciation, which is needed to offset the positive impact on the trade balance of higher interest income or more favorable trade prices, respectively (Lane and Milesi-Ferretti 2002).

With these three plausible regressors in mind, we proceed in this paper by estimating the level of *BEER* with the specification used by Faruquee (1995) and Lane and Milesi-Ferretti (2004), so that the value of *BEER*-based equilibrium is given by:

$$q_{it}^{BEER} = \mu_i + \alpha_1 gdp_{it} + \alpha_2 nfa_{it} + \alpha_3 tot_{it}, \quad (2)$$

where all explanatory variables are expressed relative to US values, given our focus on the bilateral exchange rates against the US dollar.

¹ A caveat to our analysis is that the fundamental information embedded in equilibrium exchange rate estimates might not be available in real time. However, using latest available instead of real time data does not necessarily imply a better forecasting performance of fundamental models (Faust et al. 2003). Moreover, as discussed by Sarno and Valente (2009), the weak predictive ability of exchange rate models is caused rather by poor model selection than the limited real-time availability of macroeconomic data.

The literature on equilibrium exchange rates also considers other potential regressors in the context of *BEER* equations, such as interest rate differentials or fiscal variables (e.g. MacDonald 1998; Fidora et al. 2021). We restrict our model to the three variables listed above, because they are the most relevant for the long run, while fiscal and monetary variables matter more for exchange rate fluctuations over the business cycle.

It is worth noting that parameters α_1 , α_2 and α_3 in model Eq. 2 are the same for all currencies, indicating that we use panel data to establish the relationship between the real exchange rate and fundamentals. This choice to assume homogeneity across currencies is motivated by two primary considerations. First, the FX forecasting literature is unambiguous that using panel data delivers better forecasts than individual country models (see the recent meta-analysis of Jackson and Magkonis 2024). Second, individual country *BEER* coefficient estimates often have the wrong sign or unrealistic magnitude, which raises questions about the reliability of *BEER* estimates derived using time-series models.²

3 Portfolio Construction

The next step in our study consists in creating FX portfolios that exploit the information content of equilibrium exchange rate misalignment measures. Our aims are twofold. The first is to compare the performance of such portfolios, in which currencies are sorted on the basis of the size of their exchange rate misalignment against the US dollar, relative to standard benchmarks of the FX trading strategies literature. The second is to verify how to boost the performance of the carry trade strategy, by incorporating any predictable convergence between exchange rates and their corresponding equilibria.

Technically, the starting point is the same as in the literature surveyed in the introduction. At the end of each quarter, denoted by subscript t , currencies are ranked according to signals (x_{it}), which are determined by a trading strategy. In what follows we take the view of a US portfolio manager allocating financial resources across G10 currencies. Irrespective of the chosen strategy, the portfolio is dynamically rebalanced each quarter, with buying and selling decisions based on the strength of the signals for the currencies under consideration.

To understand why some signals may lead to good or poor investment decisions, let us describe the two components of excess returns, the first related to exchange rate predictability and the second to interest rate differentials. To this aim we introduce the following notation. S_{it} denotes the spot mid-rate of currency i against the USD, which means that an increase represents an appreciation of currency i . F_{it} is defined as the one-quarter ahead forward. All variables are measured as the closing price on the last day of quarter t . Given the above notation, the excess return on the long position in currency i is equal to:

$$R_{i,t+1} = \frac{S_{i,t+1} - F_{it}}{S_{it}}. \quad (3)$$

² These results are available upon request

This measure of return can be further decomposed into a risky component, which is related to the currency return R^{ER} , and a certain component, i.e. the forward premium R^{FP} . In particular, the following expression holds:

$$R_{i,t+1} = \frac{S_{i,t+1} - S_{it}}{S_{it}} + \frac{S_{it} - F_{it}}{S_{it}} = R_{i,t+1}^{ER} + R_{i,t+1}^{FP}. \quad (4)$$

This decomposition, which is discussed in detail for a broader class of assets by Kojien et al. (2018), indicates that a potential trading strategy may consist in predicting exchange rate movements and ignoring the forward premium. This is the case, for example, for momentum strategies, which were popularized for the FX market literature by Menkhoff et al. (2012b). Exchange rate predictions based on this approach foresee the continuation of recent market trends, hence currencies are ranked in accordance to their recent performance. For our benchmark, we calculate returns relative to the previous quarter, as in Barroso and Santa-Clara (2015) or Della Corte et al. (2016). Value strategies also sort currencies by predicting exchange rate movements. In this case, however, the currencies that are expected to appreciate are the ones that previously performed poorly, because they should recover their original value. Following Asness et al. (2013); Barroso and Santa-Clara (2015) and Menkhoff et al. (2017), we calculate the signal as the five-year growth rate of the real bilateral exchange vs. the US dollar. Finally, carry trade strategies take a completely opposite perspective, as currencies are sorted exclusively on the basis of their forward premia while exchange rates movements are ignored (Lustig et al. 2011; Bekaert and Panayotov 2020). As benchmark we shall use the naïve version, i.e. that is not adjusted for economic fundamentals. It can be noted that all three above strategies share however a fundamental common assumption, i.e. that the Uncovered Interest Parity condition is violated (see Afat and Frommel 2021; Cheung and Wang 2022; Engel et al. 2022, for the most recent evidence on the “Famapuzzle”), since under this condition exchange rate movements would offset forward premia and there would be no profitable opportunities.

To summarize, the signals for the benchmark momentum (M), carry (C) and value (V) strategies are defined as follows:

$$\begin{aligned} x_{it}^M &= s_{it} - s_{i,t-1}, \\ x_{it}^C &= s_{it} - f_{it}, \\ x_{it}^V &= -(q_{i,t-1} - q_{i,t-20}). \end{aligned}$$

We turn next to propose two new strategies. The first FX strategy that we design and label $EqER$, relies exclusively on the concept of equilibrium exchange rate. In that case the signal is simply calculated as the log deviations of the actual real exchange rate from the equilibrium level:

$$x_{it}^{EqER} = q_{it}^{EqER} - q_{it} \quad (5)$$

where $EqER \in \{PPP, BEER\}$. A strategy based on this criterion will be short in overvalued currencies and long in undervalued currencies, neglecting, the existence of a forward premium.

The alternative strategy that we design, labelled *HL*, is based on the paradigm that exchange rates adjust to their equilibria slowly. More specifically, we assume that each bilateral rate against the US dollar is expected to return to its respective equilibrium according to the following log-linear process:

$$E_t s_{i,t+1} - s_{it} = \delta_i (q_{it}^{EqER} - q_{it}). \quad (6)$$

In such case the signal is a mixture of the above exchange rate forecast and of the forward premium:

$$x_{it}^{HL} = \delta_i (q_{it}^{EqER} - q_{it}) + (s_{it} - f_{it}). \quad (7)$$

Note that the forecast formula Eq. 6 implicitly assumes that the nominal exchange rate, and not relative prices, drives the required real exchange rate adjustment. This is in line with the empirical evidence for floating currencies of developed countries presented e.g. by Cheung et al. (2004) and Ca' Zorzi and Rubaszek (2020).³ The technical difficulty with Eq. 6 is how to set the value of parameter δ_i . One option is to use panel data estimation techniques, as suggested e.g. by Mark and Sul (2012). However, in this study we explore the recent contribution by Ca' Zorzi et al. (2016) and Ca' Zorzi and Rubaszek (2020), suggesting that it is simpler and more effective to calibrate rather than estimate the adjustment parameter, given the size of estimation error in small samples. To see the relevance of this choice, we choose such parameter at two fairly distant values. In one case it is calibrated under the assumption that half of the real exchange rate adjustment takes place in 3 years (*HL3*), as suggested by the “PPP puzzle” literature and, in the other case, in 10 years (*HL10*) given the evidence cited earlier of a very weak exchange rate adjustment in the first quarter. This alternative specification, while much closer to the assumption of the random walk model, still allows us to take into account, in a conservative way, that exchange rates gradually adjust to their equilibrium. Finally, note that a carry trade strategy could be viewed as the limit case of a half life strategy under the assumption that exchange rates do not adjust to their equilibria ($\delta = 0$). The relative performance of these three alternative strategies offers valuable insights into whether foreign exchange investors, who can hold large open positions in the FX market for extended periods, should consider a long-term perspective on equilibrium exchange rates in their portfolio decisions. In the next step, the signals from each method are used to construct weights for the FX trading strategy. In the baseline setup, we use rank-based weights, as proposed by Asness et al. (2013) and subsequently applied by Kroencke et al. (2014) and Dahlquist and Hasseltoft (2020). In this method, weights are equal to:

$$w_{it}^{\text{Rank}} = c \left(\text{rank}(x_{it}) - \sum_{i=1}^N \text{rank}(x_{it}) / N \right), \quad (8)$$

where N denotes the number of currencies and c is a scaling factor ensuring that an investor's short and long positions are the same and amount to one unit. The advantage of the above weighting scheme is that it delivers weight w_{it} characterized by lower

³ The dominant role of nominal exchange rate adjustment in restoring PPP cannot be taken for granted, especially in a high inflation environment (see Engel and Morley 2001, for a theoretical framework).

sensitivity with respect to extreme values of signal x_{it} compared with the alternative, more commonly used linear scheme:

$$w_{it}^{\text{Lin}} = c(x_{it} - \bar{x}_t), \quad (9)$$

where \bar{x}_t is the average value of the signal across currencies in period t . We also use a method that sorts currencies into three baskets based on signal x_{it} , forming a portfolio that is short (long) in currencies from the bottom (top) basket. This weighting scheme, which we call *MinMax*, is widely established in the literature and is used, among others, by Lustig et al. (2011); Della Corte et al. (2016), and Colacito et al. (2020). In our study, we use these two alternative weighting schemes for a robustness check of our baseline results, which is discussed in the sensitivity analysis section.

Finally, given weights w_{it} and excess returns $R_{i,t+1}$, we compute portfolio returns:

$$R_{t+1} = \sum_{i=1}^N w_{it} R_{i,t+1}. \quad (10)$$

and analyze their risk-return characteristics.

It can be noted that, since the sum of weights is zero and returns are expressed in USD terms, the return R_{t+1} denotes remuneration above the US risk-free rate.

4 Data

Our database consists of quarterly and daily data, the former to recursively estimate equilibrium exchange rates and the latter to evaluate the performance of alternative trading strategies.⁴ We consider the group of ten advanced economies that issue so-called G10 currencies, namely Australia (AUD), Canada (CAD), Switzerland (CHF), the euro area (EUR),⁵ the United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK) and the United States (USD) over the period 1975:Q1–2020:Q4. This choice is due to the following reasons. First, the G10 sample ensures high FX market liquidity and low transaction costs, which makes the analyzed trading strategies relevant in practice. Second, this sample minimises the role of country default risk. Third, the choice of G10 currencies avoids the arbitrariness of choosing ourselves the pool of currencies in the portfolio. Fourth, it helps us to relate our results to the existing literature and the recent studies focusing on trading strategies (Della Corte and Tsiakas 2012; Dahlquist and Hasseltoft 2020; Opie and Riddiough 2020) or exchange rate forecasting (Ca' Zorzi et al. 2022; Engel and Wu 2023). Finally, the choice of these countries is justified by the sufficient availability of macroeconomic data to conduct a meaningful evaluation exercise and that their currencies freely floated for most of the sample.⁶

⁴ We use daily data to calculate spot and forward rates at the end of each quarter.

⁵ For the period before 1999, we define euro area, where appropriate, as a *PPP* GDP-weighted average of the eleven founding member states.

⁶ G10 currencies are usually classified as floaters (e.g. Ilizetzi et al. 2019), albeit some of them were not freely floating for the entire period from 1975.

The panel of quarterly macroeconomic data for nine G10 countries (all but US) is constructed in the identical way as in Ca' Zorzi et al. (2022), with the only difference that the focus is on end-of-period bilateral exchange rates against the US dollar instead of effective exchange rates. To derive a real measure of the exchange rate, we deflate the nominal series by the respective consumer price index, while bearing in mind that the choice of the deflator might not be innocuous (Fidora et al. 2021). Our proxy for the Balassa-Samuelson effect, the log of *per capita* GDP, is computed by adjusting real GDP, expressed in *PPP* terms, for population size. As the latter series is only available at annual frequency, we derive quarterly data using cubic splines. Net foreign assets are taken from the IMF Balance of Payments Statistics and complemented, in some cases, with data from the External Wealth of Nations database of Lane and Milesi-Ferretti (2018) to improve the historical coverage of the data. They are then expressed as a share of GDP. Terms-of-trade series are constructed as the log for ratio of export to import deflators for goods and services. All series are seasonally adjusted and calculated as differences against US values, given our focus on the bilateral exchange rates against the US dollar.

As regards the daily data for spot S_{it} and forward F_{it} rates (bid, mid and ask), their values are retrieved from the Refinitiv Eikon database.

5 Results

In this section we present the main empirical results of our study, including the computation of equilibrium exchange rate estimates and validation of their usefulness to predict nominal exchange rates and generate well-performing currency portfolios.

5.1 Equilibrium Exchange Rate Estimates

The natural starting point is to derive bilateral equilibrium exchange rate series for all G10 currencies against the US dollar on the basis of the two methodologies outlined earlier. This is achieved in two ways, either employing the full dataset or, in a pseudo-real time data mode, using historical data available at each given point in time. Figure 1 illustrates what this implies for the *PPP* model. The full sample equilibrium, depicted by the dotted line, is constant for all observations as it is the mean of the real exchange rate for the period between 1975:Q1 and 2020:Q4. The recursive equilibrium, shown by the dashed line and calculated with an initial estimation window of 20 years, evolves over time as incoming observations gradually affect the recursive sample mean. In most cases this recursive mean is stable and not very distant from the full-sample *PPP* value.⁷

The *BEE R* model postulates a positive relationship between the real exchange rate and macroeconomic fundamentals. We estimate the parameters of the panel regression

⁷ An alternative to the recursive estimation scheme is the rolling window setup. While the recursive scheme is more effective at handling parameter estimation errors, the rolling window setup is preferable when model parameters vary over time. Determining the relative importance of these effects is an empirical question, which Ca' Zorzi et al. (2022) addressed in their sensitivity analysis. Their findings suggest that the recursive scheme slightly outperforms the rolling window setup in terms of forecast accuracy, which is the primary reason for our choice in this investigation.

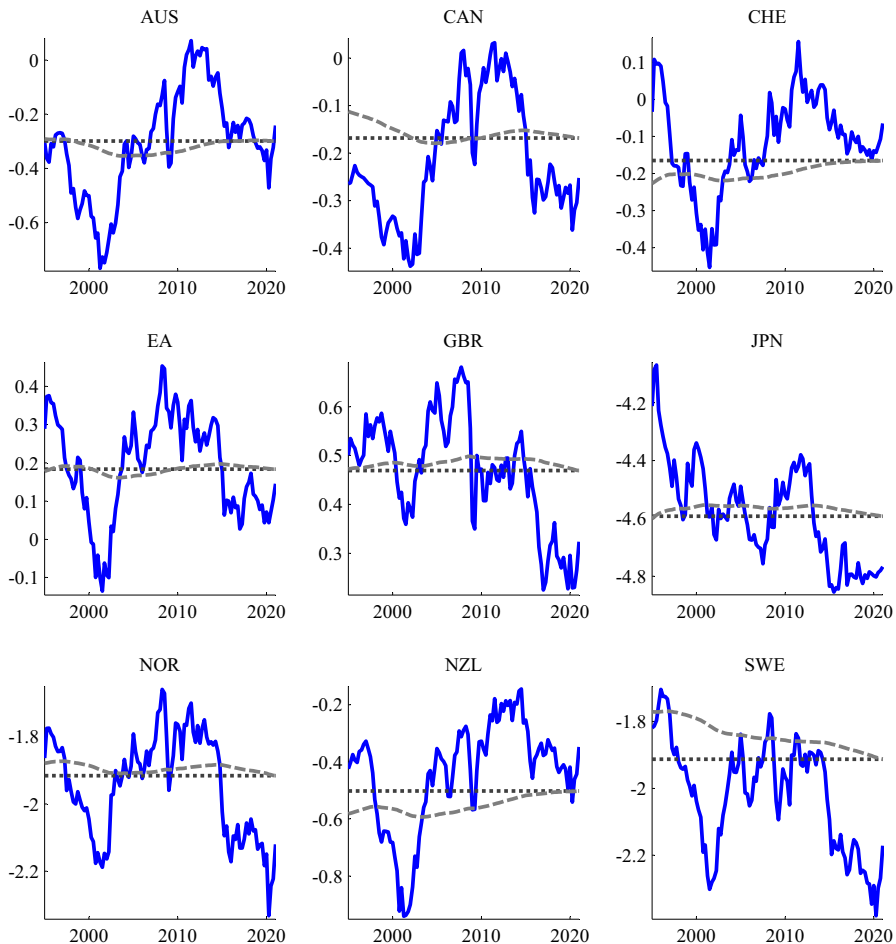


Fig. 1 PPP-based equilibrium exchange rates. Notes: The figure presents the log of actual real USD exchange rates (solid line) and its equilibrium values (dotted and dashed lines). The dotted and dashed lines denote full and recursive sample estimates of the equilibrium exchange rates, respectively

Eq. 2 to determine the strength of this relationship. However, since exchange rate movements could have a feedback effect on the right-hand-side variables and some of the regressions may be non-stationary, we estimate the empirical model with the fully-modified least squares estimator proposed by Phillips and Hansen (1990). The recursive estimates shown in Fig. 2 are already informative. While the signs of the parameters align with economic theory, the strength of the link the exchange rate and the three explanatory variables has weakened over time. This pattern may reflect the influence of evolving institutional factors, such as the scale of economic integration, monetary policy frameworks, and regulatory changes, on the relationship between the real exchange rate (RER) and economic fundamentals (Fidora et al. 2021). An alternative explanation is that, in the long run, the real exchange rate is stationary, consistent with the PPP theory. Consequently, the impact of economic fundamentals on

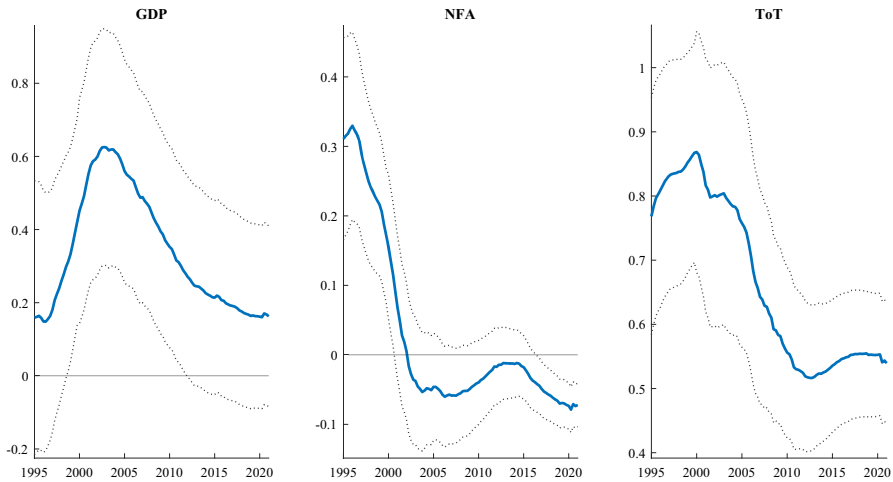


Fig. 2 Recursive estimates of *BEER* regressions. Notes: Recursive estimates of the *BEER* model (Eq. 2). The dotted lines denote the 95% confidence intervals

the real exchange rate may be short-lived and dependent on specific sample periods. For instance, Engel and Wu (2023) show that only one fundamental consistently exhibits predictive power for exchange rates: the real exchange rate itself.

The impact of this parameter variability can be detected also by the differences between full sample and recursive *BEER* estimates (Fig. 3). This means that incoming information has a greater impact for the *BEER* than the *PPP* estimates, which explains why the former is more volatile. There is also an important role for model uncertainty, since in some cases the assessments of over- or under-valuation are not robust across the two models.

5.2 Time Series Predictability

To reach the next milestone in our analysis we validate if equilibrium exchange rate models help to predict nominal exchange rates for horizons between one quarter and three years. The models are estimated using recursive samples, where the first set of forecasts is produced with models estimated over the sample 1975:Q1–1994:Q4 for the period 1995:Q1–1997:Q4.⁸

Forecast accuracy is evaluated with a standard ex-post evaluation criterion, i.e. the root mean squared forecast error (RMSFE). In Table 1 we report the RMSFE as a ratio of the same statistic for the random walk, so that values below unity indicate cases when such benchmark is beaten. The results confirm that reasonably calibrated half-life models ensure time series FX predictability as in Ca' Zorzi and Rubaszek (2020). Irrespective of the concept of equilibrium exchange rate employed, models

⁸ This procedure is repeated with samples ending in each quarter from the period 1995:Q1–2020:Q3. As a result, one-quarter ahead forecasts are evaluated on the basis of 104 observations, two-quarter ahead forecasts on the basis of 103 observations and so forth, with the 12-quarter ahead forecasts comprising of 93 observations.

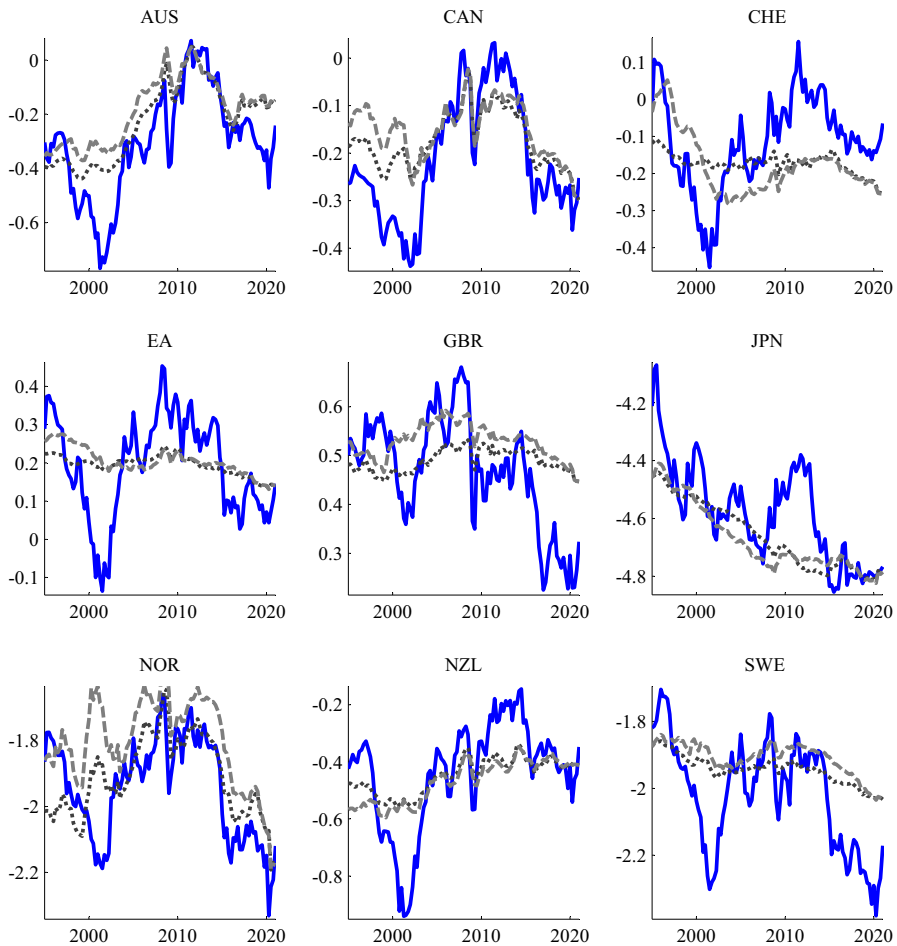


Fig. 3 BEER-based equilibrium exchange rates. Notes: As in Fig. 1

that assume a snail's pace adjustment, i.e. $HL = 10$, perform particularly well also at short horizons. The version of the model based on PPP, $HL10_{PPP}$, outperforms the random walk at all horizons. This confirms the recent findings of the (time series) FX literature on the predictive power of the PPP model.

5.3 FX Strategies Performance

Next, we present the performance of our two proposed FX strategies. This is done in multiple steps, i.e. by (i) comparing their excess returns with those achieved with three standard benchmark strategies, i.e. momentum (M), carry (C) and value (V) strategies; (ii) by decomposing excess returns to understand the origin of returns and (iii) by assessing their performance in terms of higher moments and additional metrics, such as the Sharpe ratio.

Table 1 Root mean squared forecast error (RMSFE) for half-life forecasts

	PPP				3Y	BEER				
	1Q	2Q	1Y	2Y		1Q	2Q	1Y	2Y	3Y
Half-life at 3Y										
AUD	0.996	0.987	0.973	0.931	0.903	0.991	0.980	0.954	0.895*	0.856*
CAD	0.997	0.991	0.994	0.970	0.926	1.005	1.006	1.014	0.994	0.957
CHF	0.997	0.987	0.965	0.929	0.939	1.016	1.031	1.052	1.067	1.089
EUR	0.987	0.971	0.937*	0.871**	0.821**	0.992	0.980	0.952	0.899*	0.855*
GBP	0.990	0.980	0.969	0.934	0.919	0.995	0.987	0.980	0.949	0.953
JPY	0.983	0.956*	0.910**	0.851***	0.812**	0.987	0.966	0.934	0.893*	0.865*
NOK	0.994	0.991	0.992	0.961	0.931	1.017	1.029	1.037	1.021	1.027
NZD	1.000	0.992	0.968	0.919	0.873*	0.992	0.980	0.947	0.865**	0.789**
SEK	1.010	1.016	1.027	1.029	1.041	1.001	0.998	0.993	0.966	0.958
Half-life at 10Y										
AUD	0.995	0.989	0.979	0.955*	0.933*	0.994	0.988	0.976*	0.949**	0.927**
CAD	0.995	0.989	0.983	0.963*	0.940*	0.999	0.997	0.995	0.981	0.964
CHF	0.996	0.989	0.976	0.953*	0.947*	1.002	1.004	1.006	1.005	1.008
EUR	0.994*	0.986*	0.971**	0.942**	0.916***	0.995	0.989	0.977*	0.952**	0.929**
GBP	0.995	0.990	0.983	0.966**	0.955**	0.996	0.992	0.986	0.970**	0.966*
JPY	0.992**	0.981**	0.960**	0.932***	0.909***	0.994*	0.985**	0.970*	0.949**	0.930**
NOK	0.996	0.993	0.989	0.974*	0.958*	1.002	1.002	0.999	0.984	0.980
NZD	0.996	0.990	0.977	0.949**	0.922**	0.995	0.990*	0.977*	0.943**	0.910***
SEK	0.997	0.994	0.991	0.981	0.976	0.997	0.993	0.987	0.971	0.961

Notes: The table shows the ratios of the RMSFE of the HL models presented in Eq. 6 divided by the RMSFE of the random walk benchmark at different forecast horizons. Values below unity indicate thus indicate that the HL model is more accurate than the random walk. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Diebold-Mariano test, where the long-run variance is calculated with the Newey-West method

The comparison of annualized mean returns is shown in the third row of Table 2. Among the benchmarks, *C* is the best performing strategy, with an average return of 3.38%, being above both the *V* (2.20%) and *M* (-0.72%) strategies. Both *EqER* strategies generate positive excess returns (1.61% for *PPP* and 3.19% for *BEER*) but not enough to beat the *C* strategy. This finding is intuitive, considering that such strategies are successful in exploiting the cross-sectional predictability of exchange rates but, at the one quarter horizon, the exchange rate adjustment is too weak to outperform gains that can be extracted from the forward premium. The *HL* strategies, which instead simultaneously exploit the predictive power of equilibrium exchange rates and the forward premium, guarantee stronger average returns than the pure *EqER* strategies. Moreover, in three out of four cases they also generate higher returns than carry. Indeed, the more conservative of the two *HL* versions, i.e. the one which assumes a snail's pace exchange rate adjustment (*HL10*), outperforms the *C* strategy more decisively, achieving for both the *PPP* and *BEER* versions, annualized mean returns above 4%. Additional insights can be gained by assessing the stability of the performance of the two proposed (*EqER* and *HL*) and of the three benchmark strategies (*M*, *C* and *V*).

Table 2 Performance of FX strategies

	Benchmarks			PPP-based			BEER-based		
	M	C	V	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>
Minimum	-8.39	-16.74	-10.25	-11.90	-14.96	-17.85	-19.49	-17.56	-17.40
Maximum	14.88	9.37	10.14	10.21	10.50	10.61	9.47	10.35	10.61
Mean return	-0.72	3.38	2.20	1.61	3.00	4.03	3.19	3.67	4.16
exchange rate	-1.12	-0.22	3.11	2.17	1.67	0.87	2.55	1.27	0.78
forward premium	0.40	3.59	-0.91	-0.56	1.34	3.16	0.64	2.41	3.38
Std. Dev.	7.53	8.34	7.82	6.80	7.65	8.52	7.63	8.56	8.90
Skewness	0.46	-1.27	0.03	-0.18	-0.96	-1.20	-1.21	-1.03	-1.13
Kurtosis	1.57	2.83	0.06	1.18	3.46	3.45	6.25	2.71	2.54
Sharpe ratio	-0.10	0.41	0.28	0.24	0.39	0.47	0.42	0.43	0.47
Sortino ratio	-0.14	0.57	0.45	0.37	0.58	0.69	0.64	0.63	0.68
Max. Drawdown	43.21	16.94	14.06	12.40	13.61	17.41	12.22	15.10	15.67
Turnover	26.94	2.91	7.65	4.91	4.97	4.02	5.86	4.48	3.23

Notes: The table presents performance statistics over the period 1995Q1 - 2021Q1. Weights are calculated using rank-based method (Eq. 8). Mean and standard deviations are expressed in annualized terms. The decomposition of the mean return is described by Eq. 3. Turnover relates to the average absolute value change in currency weight in a portfolio Δw_{it} . *M*, *C* and *V* stand for momentum, carry and value strategies. *EqER*, *HL3*, and *HL10* stand for strategies based on equilibrium exchange rate misalignment alone (*EqER*) or a mixture of projected return based on half-life equal to three or ten years

The upper panels of Fig. 4 show that the benchmark carry portfolio rises very rapidly until the Great Financial Crisis, before experiencing a substantial correction and a slower resumption of an upward trend. The *V* and *EqER* strategies exhibit instead a more gradual upward trend throughout the entire sample. The dynamic performance of the *HL* strategies looks instead like a mixture of the *C* and *EqER* strategies. Figure 4 also reveals the poor outcome for our benchmark momentum portfolio, especially in the second part of the sample.

Beyond performance, it is key to understand what generates excess returns for each proposed portfolio. To this aim, we decompose mean returns along two dimensions. First, we split mean returns between gains from spot rate movements and forward premia (see Eq. 4). The numbers in the fourth and fifth rows of Table 2 and in the bottom panels of Fig. 4 show that excess returns associated with the *C* strategy are driven by the efficient use of the forward premium. In fact, a carry investor is maximizing returns from interest rate differentials subject to a rank-based weighting scheme constraint (see Eq. 8). Instead, the returns from the *V* and *EqER* strategies are mainly driven by the presence of cross-sectional spot exchange rate predictability. The same table also shows how the *HL* strategies allow investors to profit from both the predictive content of equilibrium exchange rate models and the forward premium. Further insights are found by decomposing mean returns for each strategy in a second way, i.e. across the contribution of all individual currencies. The upper panel of Table 3 shows that the good performance of the *C* strategy is mainly driven by four currencies (NZD, AUD, SEK and JPY), whereas the positive return from *V* can be explained by only two (JPY and GBP). The gains are much less concentrated for *HL10* strategies, especially the

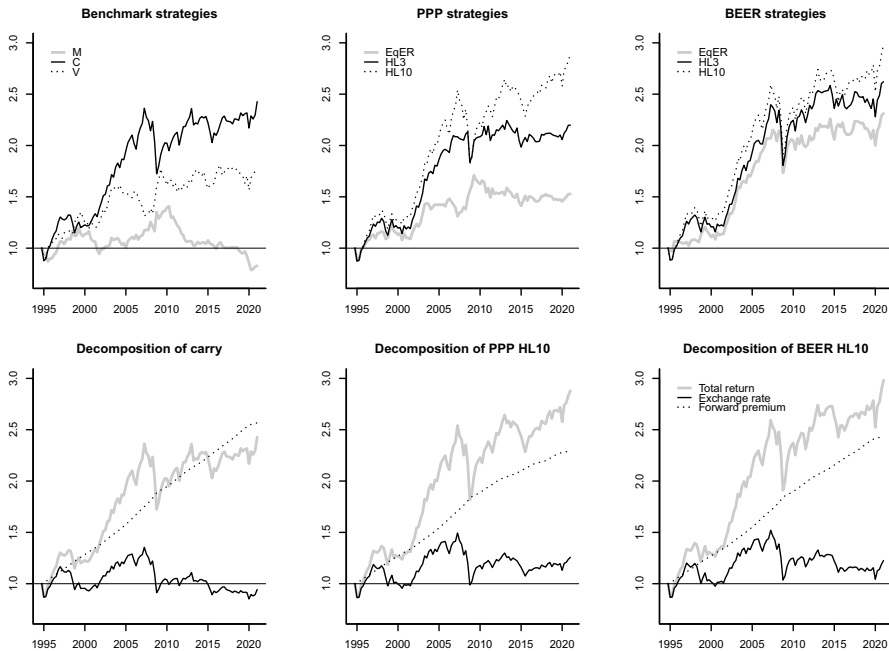


Fig. 4 FX portfolio returns. Notes: The upper panels present cumulated rate of returns for *EqER*-based and benchmark strategies. The bottom panels present excess return decomposition into spot rate predictability and forward premium, which is described in Eq. 4

one based on the *PPP* model. In this case all currencies contribute either positively or close to zero, but never negatively, to the mean return of $HL10_{PPP}$. The bottom panel of Table 3 shows that the profitability of the $HL10$ portfolios resembles much more closely that of the *C* rather than the *EqER* strategy.⁹

Finally, we assess the performance of the different strategies in terms of higher moments of excess returns and other standard metrics of portfolio performance, such as the Sharpe and Sortino ratios or maximum drawdown. As shown in Table 2, annualized standard deviations hardly differ across portfolios, varying from 6.80 for $EqER_{PPP}$ to 8.90 for $HL10_{BEER}$. The highest resulting Sharpe ratio is found for the two $HL10$ strategies at 0.47, irrespective of the underlying equilibrium exchange rate concept employed. This compares to 0.41 for the *C* strategy and 0.28 for *V*.¹⁰ As regards downside risk, skewness is strongly negative for both *HL* and carry portfolios, standing at around -1.20. The Sortino ratio is highest for $HL10_{PPP}$ at 0.69, which compares

⁹ Some notable differences remain however between the two. For instance, the *C* strategy generally indicated to be short (average weight of -5.52%) on the Swedish krona (SEK) because of its relatively low interest rate. This is in contrast to the recommendation by the $HL10_{PPP}$ (10.93%) and $HL10_{BEER}$ (11.01%) strategies to be long, in light of the signal coming from equilibrium exchange rate models of a large undervaluation during most of the sample (see Figs. 1 and 3).

¹⁰ Earlier studies often report Sharpe ratios as high as 0.75 for the best models. We explain this difference for the longer samples in their studies and/or reliance on a broader sets of currencies (see, e.g., Colacito et al. 2020; Dahlquist and Hasseltoft 2020).

Table 3 Portfolio return decomposition

	USD	EUR	JPY	GBP	CHF	CAD	AUD	NZD	SEK	NOK
Total return contribution, i.e. annualized mean value of $w_{it} R_{i,t+1}$										
Momentum	0.00	-0.09	0.05	0.11	-0.34	-0.22	-0.39	0.07	0.66	-0.55
Carry	0.00	0.09	0.67	0.07	0.02	-0.13	0.87	1.08	0.76	-0.00
Value	0.00	-0.01	0.86	0.77	0.07	0.07	0.16	0.11	-0.03	0.22
PPP EqER	0.00	0.26	0.84	-0.24	0.30	0.56	0.32	-0.37	-0.07	-0.02
PPP HL3	0.00	0.21	0.62	0.15	0.23	0.23	1.00	0.09	0.26	0.23
PPP HL10	0.00	0.30	0.49	0.35	0.16	0.13	1.21	0.66	0.80	0.00
BEER EqER	0.00	0.17	1.01	0.16	-0.43	0.19	1.46	0.43	0.34	-0.11
BEER HL3	0.00	0.19	0.67	0.31	-0.01	-0.06	1.03	1.08	0.32	0.20
BEER HL10	0.00	0.21	0.64	0.27	0.16	-0.11	1.07	0.89	0.89	0.22
Average weight, i.e. mean value of w_{it} ($\times 100$)										
Momentum	-0.50	-1.71	-4.76	-0.34	0.80	1.26	1.79	2.70	0.65	0.11
Carry	4.38	-12.91	-29.60	7.89	-31.35	2.02	23.73	29.83	-5.52	11.54
Value	-6.29	-1.49	5.22	5.30	-6.29	0.34	-8.19	-10.63	16.42	5.60
PPP EqER	0.50	-4.61	2.55	-1.03	-17.79	7.81	-2.17	-23.35	30.67	7.43
PPP HL3	0.65	-13.37	-10.10	5.75	-31.43	6.74	9.18	-6.51	29.07	10.02
PPP HL10	-2.17	-19.01	-24.27	7.12	-31.81	3.62	22.51	16.72	10.93	16.34
BEER EqER	-6.59	-5.75	-23.05	7.73	-19.39	6.67	17.71	-15.89	16.34	22.21
BEER HL3	-7.12	-12.61	-31.66	9.26	-28.61	4.91	28.23	5.07	11.01	21.52
BEER HL10	-3.16	-16.04	-32.50	9.71	-30.21	2.70	29.45	23.05	1.26	15.73

Notes: The upper panel of the table presents the contribution of each currency to mean return, which is presented in the third row of Table 2. In turn, the lower panel of the table provides the average weight calculated with formula Eq. 8

to 0.57 for C . The maximum drawdown statistics is comparable for the C and HL strategies, standing at around 15%. These findings confirm the overall strong relative performance of the HL approaches, in general, and of the $HL10$ specification, in particular. Finally, the bottom row of Table 2 highlights that the turnover of the $EqER$ and HL is moderate. The relevant statistics ranges between 3% and 6%, i.e. it is somewhat lower than the V strategy's turnover but slightly higher than for the C strategy. As a result $EqER$ and HL investors are holding similar positions for many quarters, hence these strategies can be classified as cross-sectional bets.

5.4 FX Portfolios Features

One way to examine the two proposed FX strategies is to review their resemblance to the three standard benchmarks: M , C and V . As discussed in the introduction, $EqER$ and V signals should be closely related, as they both exploit evidence of currency undervaluation. HL signals should instead share both features of V and C signals, since the half-life strategy exploits both undervaluation opportunities and the forward premium. To assess this both qualitatively and quantitatively, we estimate the following

Table 4 Relationship between *EqER*-based and benchmark signals

	<i>PPP</i> -based			<i>BEER</i> -based		
	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>
Momentum	-0.08 (0.77)	-0.00 (0.77)	-0.00 (0.77)	-0.30 (3.37)	-0.02 (3.37)	-0.01 (3.37)
Carry	-1.81 (0.67)	0.90 (5.90)	0.97 (20.80)	-3.21 (1.18)	0.82 (5.37)	0.94 (20.22)
Value	0.53 (7.58)	0.03 (7.58)	0.01 (7.58)	0.35 (4.81)	0.02 (4.81)	0.01 (4.81)
R^2	0.56	0.56	0.83	0.46	0.47	0.84

Notes: The table presents the results of fixed effect panel regression Eq. 11 using data for G10 currencies pairs and 105 quarterly observations over the period 1994Q4–2020Q4. The values in parentheses stand for *t*-Student statistics calculated using robust Driscoll and Kraay (1998) standard errors, which account for cross-sectional and temporal dependence. This makes this method suitable to our setting, in which the time dimension of the panel is large

fixed-effect panel regression proposed by the literature (see, e.g., Della Corte et al. 2016; Colacito et al. 2020; Dahlquist and Hasseltoft 2020):

$$x_{it}^E = \alpha_i + \beta_M x_{it}^M + \beta_C x_{it}^C + \beta_V x_{it}^V + \epsilon_{it}^E, \quad (11)$$

which provides the strength of the correlation between the signals of a newly proposed strategy $E \in \{EqER, HL\}$ and the signals sent by the three standard benchmarks (M , C and V).

The results in Table 4 show how for both *EqER* strategies, irrespective of the definition of equilibrium exchange rate, the signal from the V strategy has significant explanatory power, as revealed by the estimated coefficients 0.53 for *PPP* and 0.35 for *BEER*. There is no evidence instead of a significant relationships between *EqER* and

Table 5 Relationship between returns of *EqER*-based and benchmark strategies

	<i>PPP</i> -based			<i>BEER</i> -based		
	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>
Alpha	-0.23 (0.30)	-0.09 (0.11)	0.44 (0.86)	0.71 (0.54)	0.09 (0.10)	0.39 (0.95)
Momentum	0.02 (0.37)	-0.11 (1.19)	-0.05 (1.29)	-0.29 (2.34)	-0.10 (1.70)	-0.02 (0.73)
Carry	0.11 (1.22)	0.62 (6.35)	0.97 (22.95)	0.46 (3.22)	0.88 (12.15)	1.03 (32.03)
Value	0.67 (8.27)	0.41 (4.99)	0.13 (3.37)	0.38 (3.78)	0.25 (3.90)	0.12 (3.40)
R^2	0.61	0.61	0.90	0.47	0.77	0.93

Notes: The table presents the results for regression Eq. 12, which is based on $T = 105$ quarterly observations. For convenience, we express Alpha in annual terms. The values in parentheses stand for *t*-Student statistics calculated with robust (Newey–West) standard errors

Table 6 Performance statistics - sensitivity analysis

	Benchmarks			<i>PPP</i> -based			<i>BEER</i> -based		
	<i>M</i>	<i>C</i>	<i>V</i>	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>	<i>EqER</i>	<i>HL3</i>	<i>HL10</i>
Baseline									
Mean return	-0.72	3.38	2.20	1.61	3.00	4.03	3.19	3.67	4.16
exchange rate	-1.12	-0.22	3.11	2.17	1.67	0.87	2.55	1.27	0.78
forward premium	0.40	3.59	-0.91	-0.56	1.34	3.16	0.64	2.41	3.38
Std. Dev.	7.53	8.34	7.82	6.80	7.65	8.52	7.63	8.56	8.90
Sharpe ratio	-0.10	0.41	0.28	0.24	0.39	0.47	0.42	0.43	0.47
Linear weighting									
Mean return	-0.97	3.97	2.40	2.16	3.64	4.32	3.23	4.16	4.53
exchange rate	-1.41	-0.11	3.51	2.83	1.98	0.73	2.42	1.24	0.63
forward premium	0.45	4.06	-1.11	-0.68	1.67	3.59	0.82	2.92	3.89
Std. Dev.	7.95	9.78	9.14	7.36	7.96	9.25	8.18	9.71	9.96
Sharpe ratio	-0.12	0.41	0.26	0.29	0.46	0.47	0.40	0.43	0.45
MinMax weighting									
Mean return	-0.24	4.02	2.83	1.22	2.63	4.31	3.35	3.71	4.12
exchange rate	-0.66	0.25	3.72	1.77	1.32	0.98	2.71	1.12	0.55
forward premium	0.43	3.76	-0.88	-0.55	1.30	3.33	0.64	2.58	3.56
Std. Dev.	7.78	9.22	8.23	7.62	8.96	9.43	8.50	9.52	9.68
Sharpe ratio	-0.03	0.44	0.34	0.16	0.29	0.46	0.39	0.39	0.43
2010-2020 sample									
Mean return	-4.75	1.66	0.91	-0.56	0.48	2.34	1.10	1.40	2.09
exchange rate	-4.77	-0.87	1.58	0.67	0.87	0.59	0.95	0.21	-0.17
forward premium	0.02	2.52	-0.67	-1.22	-0.39	1.75	0.15	1.19	2.25
Std. Dev.	5.76	6.13	6.78	5.13	4.79	5.12	6.42	6.16	6.70
Sharpe ratio	-0.82	0.27	0.13	-0.11	0.10	0.46	0.17	0.23	0.31
Transaction costs									
Mean	-0.98	3.11	1.95	1.34	2.73	3.76	2.93	3.40	3.89
Std. Dev.	7.54	8.34	7.82	6.80	7.65	8.53	7.63	8.56	8.90
Sharpe	-0.13	0.37	0.25	0.20	0.36	0.44	0.38	0.40	0.44

Notes: As in Table 2

C signals, which means that this strategy could add value to carry.¹¹ The results in the table also reveal that there is an inversely negative relationship between the *EqER* and *M* signals, which is also found to be significant in the case of the *BEER* equilibrium exchange rate model. This finding can be easily rationalized considering that strategies based on momentum perceive a real exchange rate appreciation as a signal of currency strength, whereas those based on equilibrium exchange rate estimates as a signal of overvaluation. The table also suggests that there is idiosyncratic information embedded in the *EqER* signals, given that the value of the R^2 coefficient is well below unity.

¹¹ The β_C estimates are however of the expected sign, which implies that currencies in high interest countries tend to be overvalued. The estimated semi-elasticities of FX misalignment with respect to the interest rate differential are plausible, amounting to 1.81 for *PPP* and 3.21 for *BEER* respectively.

As regards the regression results for the HL signals, the table confirms that they are largely explained by C and to a much lower extent by V signals. This empirical relationship is easily understandable if one notices that Eq. 7 can be transformed into:

$$x_{it}^{HL} = \delta x_{it}^{EqER} + x_{it}^C,$$

which means that the HL signal is a linear combination of the $EqER$ and C signals.

There is another complementary test to see if $EqER$ and HL strategies provide investors with opportunity of diversifying their FX portfolio than would be the case by appropriately mixing the three benchmark portfolios. This relies on running a regression between returns (rather than signals) across different strategies:

$$R_t^E = \alpha + \beta_M R_t^M + \beta_C R_t^C + \beta_V R_t^V + \epsilon_t^E. \quad (12)$$

Colacito et al. (2020) argue that a new strategy offers diversification gains if α is positive and significant. Table 5 shows that the $HL10$ is the best strategy also from this perspective since the estimates of α are positive and equal to about 0.40 p.p (albeit they are not statistically significant). The table also shows that, irrespective of the choice of equilibrium exchange rate model, HL strategies are approximately a linear combination of carry and value portfolios, with weights equal to around 1.00 and 0.12, augmented for a small idiosyncratic component.

6 Extensions and Sensitivity Analysis

In this section we present additional analyses, which extend our baseline results and help assess their robustness. These include incorporating other weighting schemes,

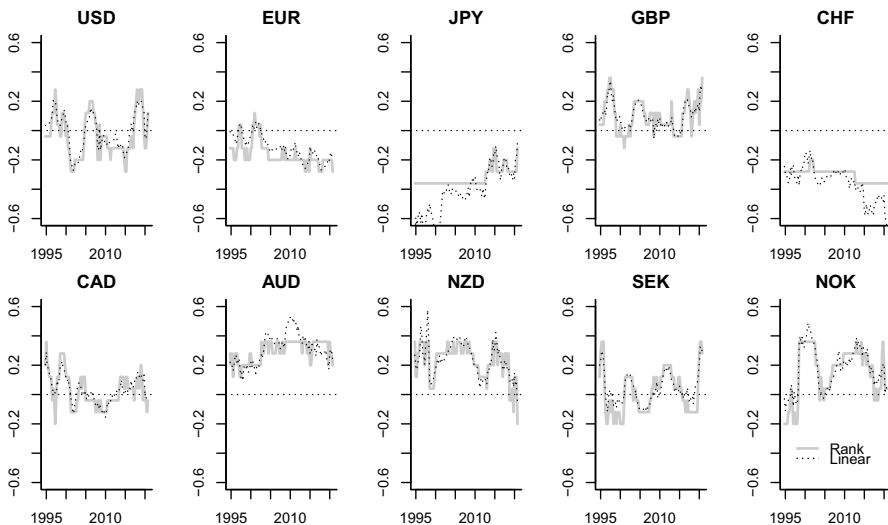


Fig. 5 Comparison of rank and linear weights. Notes: The figure presents weights of currencies in the $BEER_{HL10}$ portfolio, which are calculated with rank (gray solid line, see Eq. 8) and linear (black dotted line, see Eq. 9) methods

shortening the time-span of the evaluation sample, accounting for transaction costs and changing the assumption about the half-life parameter from model Eq. 6. In all cases, we look at how a given modification affects the key performance statistics of resulting portfolios. The outcomes of these analyses are presented in Table 6 which, for ease of comparison, contains also the baseline findings discussed in the previous section.

6.1 Other Weighting Schemes

We start by looking at the performance of currency portfolios constructed with different weighting schemes. Apart from the baseline rank-based weights, we apply two other approaches described in Section 3, which are commonly used in the literature (see eg. Lustig et al. 2011; Della Corte et al. 2016; Colacito et al. 2020). First, we use the *linear* scheme, in which the weight for a particular currency is proportional to the strength

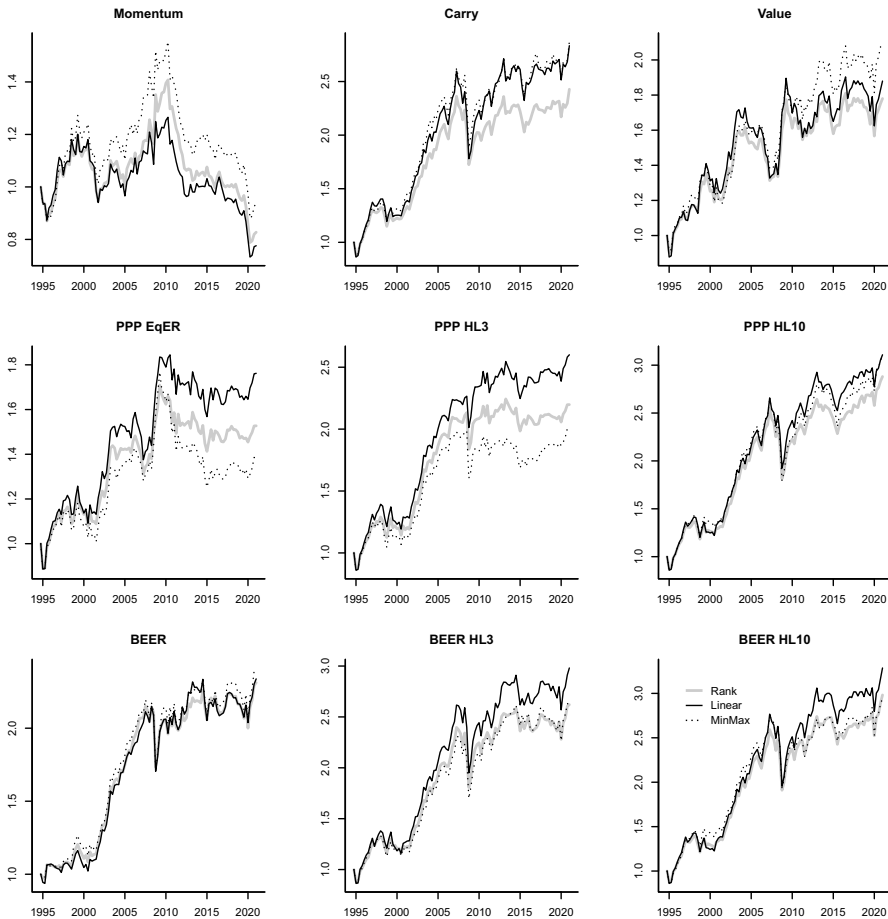


Fig. 6 Weighting scheme and FX portfolio returns. Notes: The figures present cumulated rate of returns for benchmark and *EqER*-based FX portfolios in three weighting scheme variants

of the signal. The consequence is that currencies with extremely strong signals may dominate the entire portfolio (Fig. 5). We also use the *MinMax* weighting scheme, in which portfolio long (short) weights are the same for currencies from the top (bottom) basket.

The second panel of Table 6 shows that linearly weighted portfolios deliver slightly higher mean returns than the baseline rank weighted portfolios, albeit at the cost of increased volatility, hence the resulting Sharpe ratios are broadly unchanged. The use of the *MinMax* weights has instead a slightly positive impact on the performance of the three benchmark portfolios. This is illustrated in Fig. 6, which presents the cumulative returns for all weighting schemes and portfolios. Overall, differences in the performance among the three weighting schemes are usually small. We conclude that our baseline results are not sensitive with respect to the different choices of calculating weights.

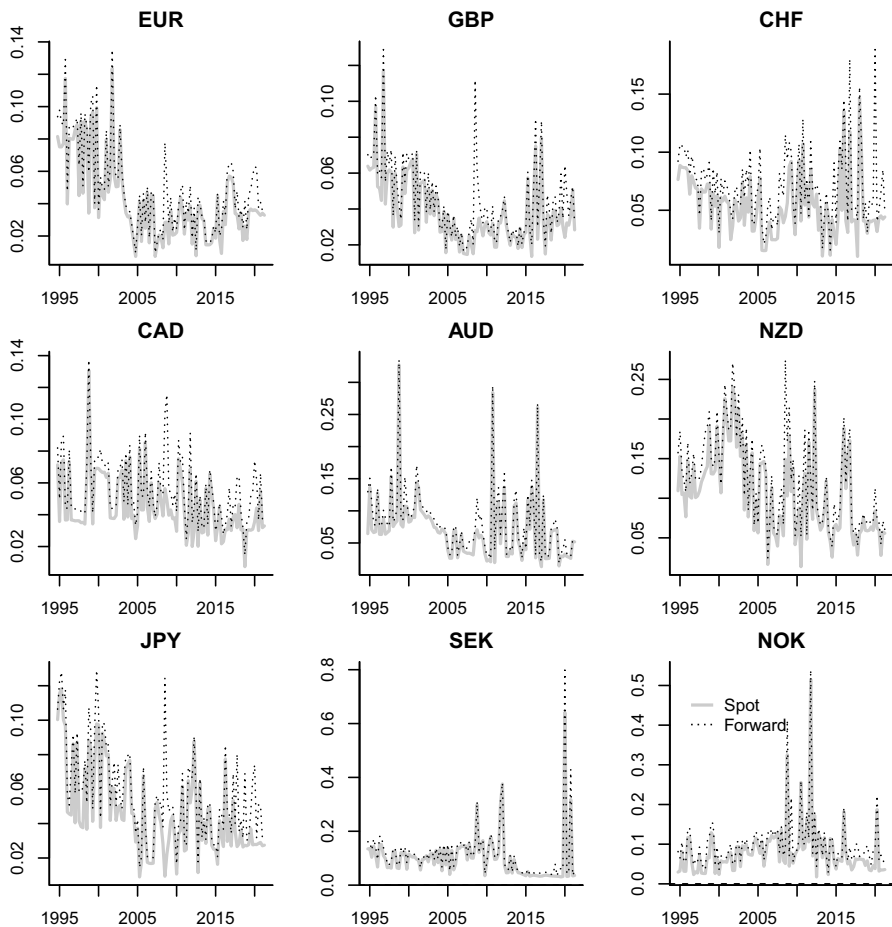


Fig. 7 The scale of transaction costs. Notes: The figures present the ask-bid spread for spot and forward rate (expressed in %)

6.2 Shorter Sample

We also analyze the performance of FX portfolios by focusing only on the shorter sample of the last 10 years. The fourth panel of Table 6 shows that the performance of the three benchmark, e.g. measured by the Sharpe ratio, worsened somewhat in comparison to the full sample. The same can be observed for equilibrium exchange rate based portfolios and for the $HL10_{BEER}$ portfolio. The main exception is the performance of the $HL10_{PPP}$ strategy, which appear more stable in time. This may indicate a greater resilience in its performance compared to the remaining strategies.

6.3 Transaction Costs

To bring our study closer to the real world, we look at how transaction costs (in the form of bid-ask spreads) affect portfolio performance. We use the quoted bid and ask

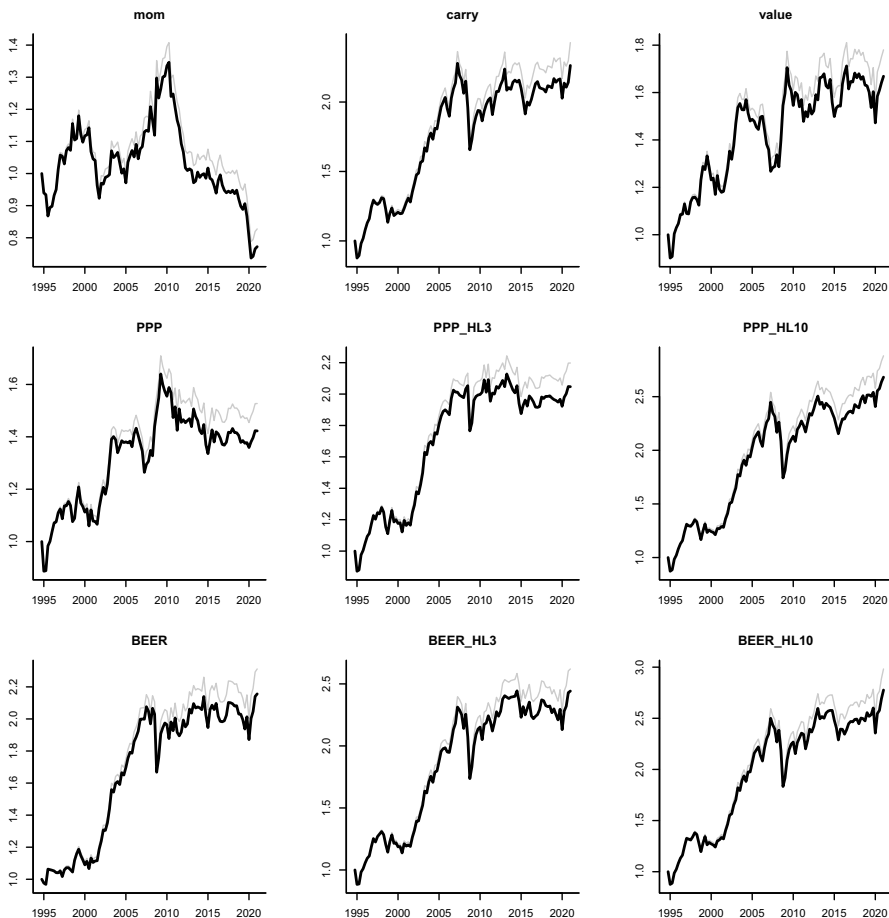


Fig. 8 The effect of transaction costs on FX portfolio returns. Notes: The figures present cumulated rate of returns for benchmark and $EqER$ -based FX portfolios in two variants: with and without transaction costs

rates, which are presented in Fig. 7, to calculate the excess returns from long and short positions with formulas:

$$R_{i,t+1}^{\text{Long}} = \frac{S_{i,t+1}^{\text{Bid}} - F_{it}^{\text{Ask}}}{S_{it}^{\text{Mid}}}, \quad R_{i,t+1}^{\text{Short}} = \frac{S_{i,t+1}^{\text{Ask}} - F_{it}^{\text{Bid}}}{S_{it}^{\text{Mid}}}.$$

Moreover, we take into account the discussion by Menkhoff et al. (2012a, 2017), who claim that quoted spreads are much higher than realized transaction costs. In particular, we follow Colacito et al. (2020) and reduce the costs arising from the bid-ask spread by 50%.

The impact of such calculated transaction costs on all trading strategies is presented in the bottom panel of Table 6 and visualized in Fig. 8. For all strategies, introducing transaction costs lowers the annual mean return by roughly 0.25 pp. and the Sharpe ratio by 0.03, whereas volatility remains virtually unchanged. This is illustrated in Fig. 8, which points to a gradually declining cumulative return due to transaction costs. Overall, apart from an expected uniform deterioration in portfolio performance, the introduction of transaction costs does not change the relative risk-return characteristics across all considered strategies.

6.4 Half-life Adjustment

Finally we evaluate if the good performance of HL strategies is robust to different half-life calibrations than those chosen in the baseline. To this aim we compare the Sharpe ratios of the HL strategies with that of C benchmark for half-lives that go from zero to infinity. The left panel of Fig. 9 illustrates how the Sharpe ratio of the HL_{PPP} strategy is close to that of the C benchmark for half-lives above 3 years, higher for half-lives above 7 years and reaches its peak value at 12 years. The right panel illustrates how

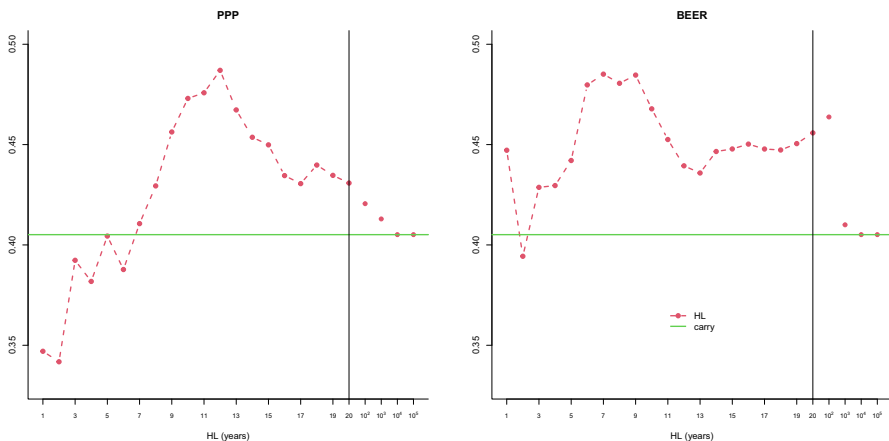


Fig. 9 Adjustment parameter and the Sharpe ratio of half-life FX portfolios. Notes: The figures present the relationship between the calibrated value of δ_i parameter in model Eq. 6, which is expressed in terms of half-life in years, and the Sharpe for HL_{PPP} and HL_{BEER} portfolios. The green vertical line denotes the Sharpe ratio of the carry strategy

the Sharpe ratio of the HL_{BEER} strategy is higher than that of the C benchmark for half-lives above 2 years and its value peaks at 7 years. The overall message that we get from this exercise is that the HL model is competitive for half-lives higher than 2 or 3 years and that its relative performance relative to the C benchmark improves even further for higher half-lives. This means that from an investor's perspective it is preferable to postulate that exchange rates adjust at snail's pace to their equilibrium than to rely on the random walk paradigm.

7 Conclusions

The primary aim of this paper has been to assess the relevance of the equilibrium exchange rate concept from an investor's perspective. Our key findings are threefold:

First, we have proposed a currency portfolio which extracts the information content from currency misalignments. We have shown that, in spite of the uncertainty surrounding the estimation of equilibrium exchange rates, such portfolio would have been profitable.

Second, we have highlighted that the performance of the proposed strategy is, in general, inferior to one based on carry trades alone. The evidence that initially exchange rates adjust only slowly toward their equilibria helps explain why carry trade strategies remain profitable.

Third, we have proposed an alternative currency strategy, labeled HL , which boosts the naïve carry trade strategy with equilibrium exchange rate estimates. We have shown how the implied portfolios, irrespective of whether we use the PPP and $BEER$ equilibrium exchange rate models, or half-lives of three and ten years, tend to perform well. Strategies based on the half-life adjustment model also change the nature of expected returns, since a significant component comes from the modeler's ability to extract the cross-sectional predictability of exchange rates. HL strategies are also an elegant method of mixing two well-known benchmark strategies, carry and value.

The main message of the paper is not to dispute the evidence that carry trades performed well in recent decades. To the contrary HL strategies largely exploit the forward premium in a similar way. What we dispute in this paper is that the success of carry trade strategies is evidence of a random adjustment of exchange rates while their success is perfectly consistent with the alternative paradigm that exchange rates gradually return to their long-run equilibria.

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