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Michał Rubaszek, Joscha Beckmann, Michele Ca' Zorzi, Marek Kwas

Boosting carry with equilibrium exchange rate estimates

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Abstract

We build currency portfolios based on the paradigm that exchange rates slowly converge to their equilibrium to highlight three results. First, this property can be exploited to build profitable portfolios. Second, the slow pace of convergence at short-horizons is consistent with the evidence of profitable carry trade strategies, i.e. the common practice of borrowing in low-yield currencies and investing in high-yield currencies. Third, the predictive power of equilibrium exchange rates may boost the performance of carry trade strategies.

Keywords: Equilibrium Exchange Rate; Carry Trade; Trading strategies.

JEL classification: F31, G12, G15

NON-TECHNICAL SUMMARY

It is a widely held view in economics that predicting future exchange rate movements is almost impossible. Two pieces of evidence are put forward to support this thesis. The first comes from the (time series) FX literature on currency forecasting, suggesting that it is preferable to assume that exchange rates follow a "random walk", and hence predict that they don't change, than using a macro model to forecast them. The second, which prevails in the FX literature on currency portfolios, points to the success of a naïve investment strategy known as "carry trade", consisting in borrowing in low-yield and investing in high-yield currencies, which treats future exchange rate movements as random. For several decades there has been a parallel quest in these two strands of the FX literature, the first aiming at forecast accuracy and the second at portfolio profitability, to outperform the respective benchmarks, the random walk forecast and the carry trade strategy. In both cases the approach was the same in spirit, i.e. to set up a model attempting to recover, either theoretically or empirically, a link between exchange rates and economic fundamentals. However, these efforts have only marginally dented the prevailing consensus that exchange rates are unpredictable.

The assumption of random exchange rates is however difficult to accept being at odds with economic theory. Two authors of the present paper have advocated for a viable alternative paradigm to the random walk to achieve greater forecast accuracy, i.e. to postulate a gradual process of convergence of the exchange rate toward its long-run equilibrium. This alternative paradigm takes a minimalist stance on the role of fundamentals and uses them only to anchor long-term equilibrium exchange rates (Ca' Zorzi and Rubaszek, 2020; Ca' Zorzi et al., 2020). Such measures can be easily derived by either assuming that real exchange rates are mean reverting to restore purchasing power (Purchasing Power Parity model, PPP) or determined by a limited set of economic fundamentals (Behavioral Equilibrium Exchange Rate model, BEER). The evidence presented in the above cited papers suggests that this paradigm is not only economically attractive, but competitive in predictive terms. In other words, it challenges the first piece of evidence that is used in the public discourse to conclude that exchange rates move randomly. In this paper we address the second piece of evidence frequently mentioned in favor of the random walk hypothesis, by reviewing the success of carry strategies. We investigate whether our alternative paradigm, stating that exchange rates are partly predictable since they gradually revert to their equilibria, performs similarly well or even boosts the performance of the carry trade strategy.

Our database consists of quarterly data, which enables us to recursively estimate equilibrium exchange rates that are instrumental for our trading strategies. We focus on ten advanced economies that issue so-called G10 currencies, namely Australia, Canada, Switzerland, the euro area, the United Kingdom, Japan, Norway, New Zealand, Sweden and the

United States over the period 1975:Q1–2020:Q4. We first calculate two sets of equilibrium exchange rate estimates, expressed in bilateral terms against the US dollar, using two standard models (PPP and BEER), and verify our claim that there is time series predictability. We then employ the tools and methods of the FX trading literature to show that accounting for exchange rate misalignments also delivers cross-sectional predictability and an FX portfolio with competitive risk-return characteristics.

Our analysis contributes to the exchange rate literature in three dimensions. First, we develop a foreign exchange portfolio strategy that only extracts the information content from currency misalignments. The size of over or under-valuation of analyzed currencies is used to derive FX portfolio weights. We show that, despite the estimation uncertainty over equilibrium exchange rates, such portfolio would have been profitable. This result is consistent with the view that exchange rates do not move randomly.

Second, we show that the performance of a portfolio based on currency misalignments, while competitive relative to other benchmarks, cannot outperform the carry trade strategy. We interpret this result as perfectly consistent with the evidence that initially exchange rates adjust very slowly to their equilibria, hence the predictable component is insufficient to outweigh the certain gains that derive from the prevailing interest rate differentials' configuration among the G10 countries.

Third, we design a currency strategy based on the hypothesis that exchange rates gradually approach their equilibria and complete half of the adjustment in either three or ten years (half-life, HL). We show that these HL strategies are strongly competitive because they exploit both forward premia and the time series predictability of exchange rates. In particular, an FX portfolio based on the hypothesis that exchange rates adjust at snail's pace, i.e. requiring ten years to complete half of the adjustment, would have generated higher expected returns and Sharpe ratios than the naïve carry trade strategy, both in the case of PPP and BEER models. This result shows how a departure from the random walk hypothesis can be instrumental for boosting a carry-based FX trade strategy. Besides the issue of performance, HL strategies profoundly change the nature of expected returns since a significant component comes from the modeler's ability to extract the predictability of spot exchange rates. We also show the generality of our results for a wide range of the half-life parameter.

The main message of the paper does not question the evidence that carry trades performed well in recent decades. To the contrary, HL strategies closely resemble carry trade strategies in practice. What we dispute is that this success provides evidence in favor of the randomness of exchange rates vis-à-vis the more plausible alternative that exchange rates gradually adjust to their equilibria.

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 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; Engel and Wu, 2021; Ca' Zorzi et al., 2020). 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., 2020).

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 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 seminal 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. Similarly, 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 suggests 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 three 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 et al., 2016; Menkhoff et al., 2017; Dahlquist and Hasseltoft, 2020; Colacito et al., 2020), our study is unique in its attempt to explicitly exploit the information content of estimated equilibrium exchange rates vs. the US dollar to construct an FX portfolio in a transparent and interpretable way. Second, we illustrate how a strategy based on equilibrium exchange rates alone underperforms relative to a carry strategy. The reason is that the predictable component of exchange rate movements at the one quarter horizon cannot outweigh the gains derived from knowing with certainty the prevailing configuration of interest rate differentials across the G10 countries. Third, we show that it is possible to build a signal that adjusts a naïve carry trade strategy for information about the expected convergence of exchange rates to their equilibria. We prove that the (time series) predictability of exchange rates boosts the performance of such portfolio and, even more importantly, it profoundly changes the nature of the realized gains, as they are shown to partly derive from the predictability of exchange rates. We also explain that the proposed strategy is an interpretable mix of carry and value strategies plus an idiosyncratic component.[1]

The main message of the paper is not to question the past good performance of carry trades, but to argue that such good performance can be also rationalized and boosted with the concept of self-equilibrating exchange rates.

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 to predict exchange rates and to design currency portfolios. Section 6 contains sensitivity analysis. Finally, Section 7 draws the main conclusions of the paper.

[1]This is in line with other popular studies, which argued that a combination of strategies may offer higher returns than each of them in isolation. For instance, Asness et al. (2013) investigate the mix of value and momentum strategies; Menkhoff et al. (2017) similarly argue that value and carry strategies are largely independent and capture distinct parts of the currency risk premium. Finally, Barroso and Santa-Clara (2015) propose a strategy that combines carry, momentum and value.

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 is a good proxy for the PPP-based equilibrium real exchange rate (q^{PPP}):

$$q_{it}^{PPP} = \overline{q}_i. \tag{1}$$

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., 2017). Our analysis includes three key fundamentals: relative per capita GDP (gdp), net foreign assets (nfa) and the terms of trade (tot).[2] As discussed in the literature, e.g. Ca' Zorzi et al. (2020), 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 Faruqee (1995) and Lane and Milesi-Ferretti (2004), so that the value of $BEER$-based equilibrium is given by:

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

where all explanatory variables are expressed relative to foreign values.

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., 2017). 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.

[2] 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.

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. Irrespectively 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:

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

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:

$$R_{i,t+1} = \frac{S_{i,t+1} - S_{it}}{S_{it}} + \frac{S_{it} - F_{it}}{S_{it}} = R^{ER}_{i,t+1} + R^{FP}_{i,t+1}. \tag{4}$$

This decomposition, which is discussed in detail for a broader class of assets by Koijen 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 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 Cheung and Wang, 2022; Engel et al., 2022, for the most recent evidence on the "Fama puzzle"), 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:

$$x_{it}^{EqER} = q_{it}^{EqER} - q_{it} \tag{5}$$

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:

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

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

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

Note that the forecast formula (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 (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 proves insightful to understand whether foreign exchange investors should incorporate a long-term view of equilibrium exchange rates in their portfolio investment choice.

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:

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

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 sensitivity with respect

[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).

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

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

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:

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

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 (Dahlquist and Hasseltoft, 2020; Opie and Riddiough, 2020) or exchange rate forecasting (Engel and Wu, 2021; Ca' Zorzi et al., 2020). 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]

The quarterly macroeconomic data are constructed in the identical way as in Ca' Zorzi et al. (2020), with the only difference that the focus is here on the bilateral and not effective exchange rates. We use the end-of-period values of each bilateral exchange rate against the US dollar. 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., 2017). Our proxy for the Balassa-Samuelson effect, *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 ratio of export to import prices. Given the quarterly frequency of our data, all series are seasonally adjusted. Finally, the daily data for spot S_{it} and forward F_{it} rates (bid, mid and ask) are retrieved from the Refinitiv Eikon database.

[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. Ilzetzki et al., 2019), albeit some of them were not freely floating for the entire period from 1975.

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.

The $BEER$ model postulates a positive relationship between the real exchange rate and macroeconomic fundamentals. We estimate the parameters of the panel regression (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 Figure 2 are already informative. While the signs of the parameters are consistent with economic theory, the economic significance of all three fundamentals has fallen over time. The impact of this parameter variability can be detected also by the differences between full sample and recursive $BEER$ estimates (Figure 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.[7]

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 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 benchmarks 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.

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). The

[7] 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.

upper panels of Figure 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 equation 4). The numbers in the fourth and fifth rows of Table 2 and in the bottom panels of Figure 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 equation 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 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.[8]

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.[9] As regards downside risk, skewness is strongly negative for both

[8]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 Figures 1 and 3).

[9]Earlier studies often report Sharpe ratios as high as 0.75 for the best models. We explain this difference

HL and carry portfolios, standing at round -1.20. The Sortino ratio is highest for $HL10_{PPP}$ at 0.69, which compares 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 fixed-effect panel regression proposed by the literature (see, e.g., Della Corte et al., 2016; Colacito et al., 2020; Dahlquist and Hasseltoft, 2020):

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

which provides the strength of the correlation between the signals of a newly proposed strategies $E \in \{EqER, HL\}$ 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 C signals, which means that this strategy could add value to carry.[10] 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

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).

[10]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.

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.

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 equation (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:

$$R_t^E = \alpha + \beta_M R_t^M + \beta_C R_t^C + \beta_V R_t^V + \epsilon_t^E. \tag{12}$$

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, shortening the time-span of the evaluation sample, accounting for transaction costs and changing the assumption about the half-life parameter from model (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 of the signal. The consequence is that currencies with extremely strong signals may dominate the entire portfolio (Figure 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 Figure 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.

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

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

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 Figure 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 Figure 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 Figure 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 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 key motivation of this paper has been to evaluate the usefulness of the concept of equilibrium exchange rates 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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Tables and Figures

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

	PPP					*BEER*				
	1Q	2Q	1Y	2Y	3Y	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*
GBB	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**
GBB	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 equation (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.

Table 2: Performance of FX strategies

	Benchmarks			PPP-based			$BEER$-based		
	M	C	V	$EqER$	$HL3$	$HL10$	$EqER$	$HL3$	$HL10$
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 equation (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.

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 (8).

Table 4: Relationship between $EqER$-based and benchmark signals

	PPP-based			$BEER$-based		
	$EqER$	$HL3$	$HL10$	$EqER$	$HL3$	$HL10$
Momentum	-0.08	-0.00	-0.00	-0.30	-0.02	-0.01
	(1.57)	(1.57)	(1.57)	(5.32)	(5.32)	(5.32)
Carry	-1.81	0.90	0.97	-3.21	0.82	0.94
	(0.44)	(3.92)	(13.82)	(1.56)	(7.09)	(26.68)
Value	0.53	0.03	0.01	0.35	0.02	0.01
	(22.94)	(22.94)	(22.94)	(8.83)	(8.83)	(8.83)
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 (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, which were calculated using robust (Arellano) and currency clustered standard errors.

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

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

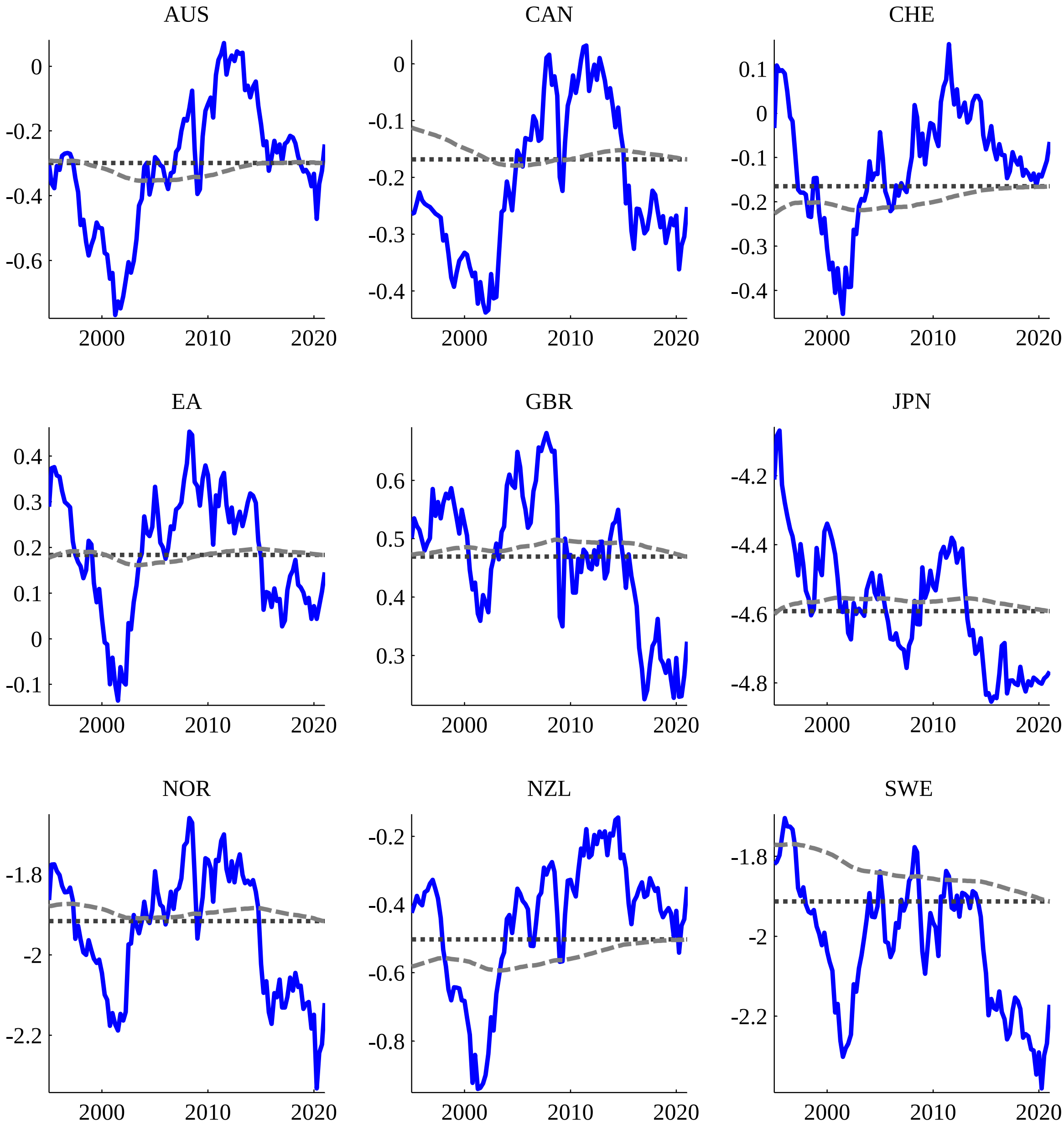
Notes: The table presents the results for regression (12), which is based on $T = 105$ quarterly observations. For convenience, we express Alpha in annual terms. The values in parentheses stand for t-Student statistics calculated with robust (Newey-West) standard errors.

Table 6: Performance statistics - sensitivity analysis

	Benchmarks			*PPP*-based			*BEER*-based		
	M	C	V	$EqER$	$HL3$	$HL10$	$EqER$	$HL3$	$HL10$
	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

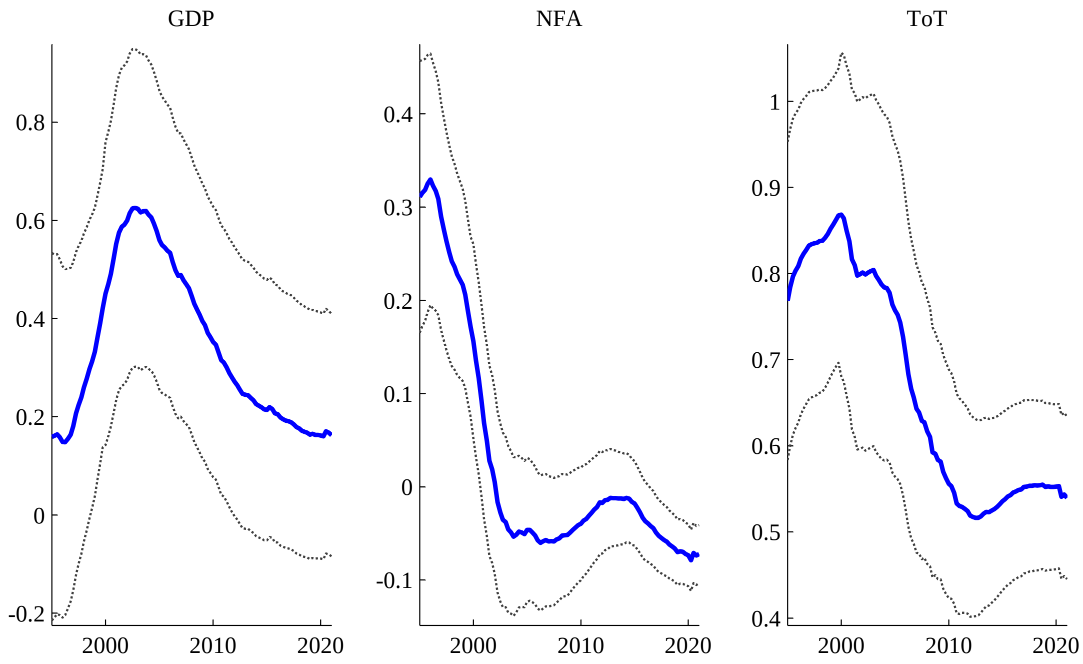
Notes: As in Table 2.

Figures

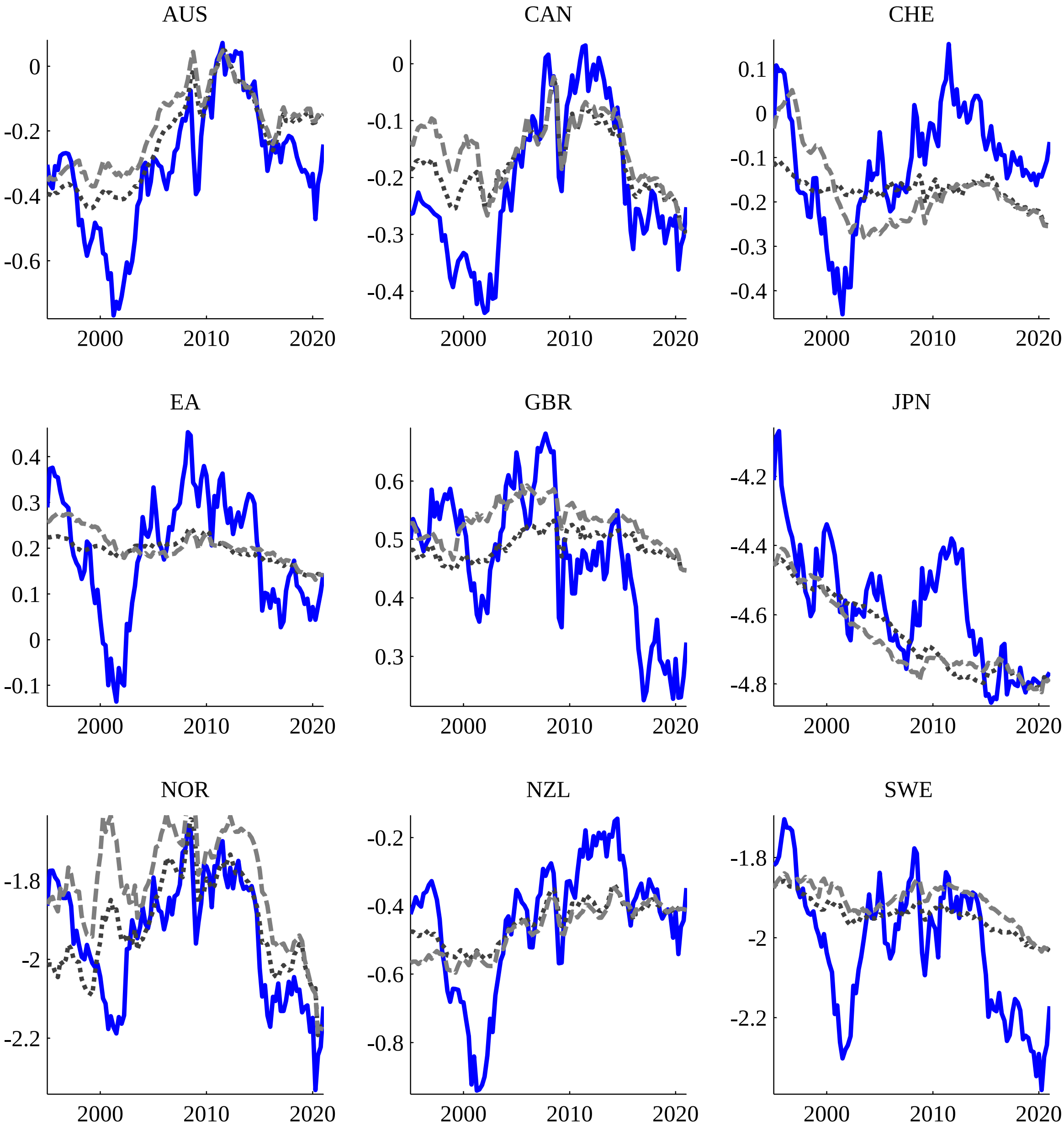


Notes: The figure presents the log of actual real USD exchange rates (solid line) and its equilibrium values (dotted and dashed lines). The dotted and dashed lines denote full and recursive sample estimates of the equilibrium exchange rates, respectively.

Figure 2: Recursive estimates of $BEER$ regressions

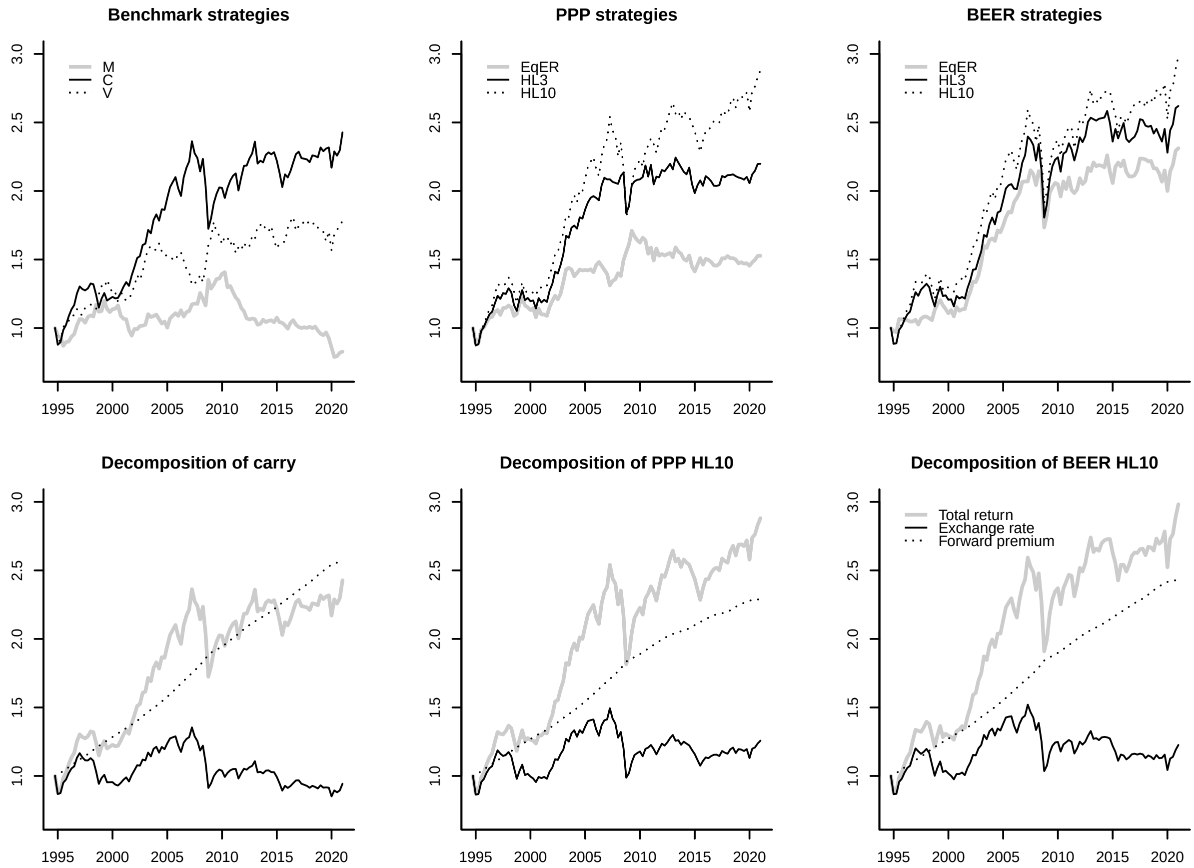


Notes: Recursive estimates of the $BEER$ model (equation 2). The dotted lines denote the 95% confidence intervals.



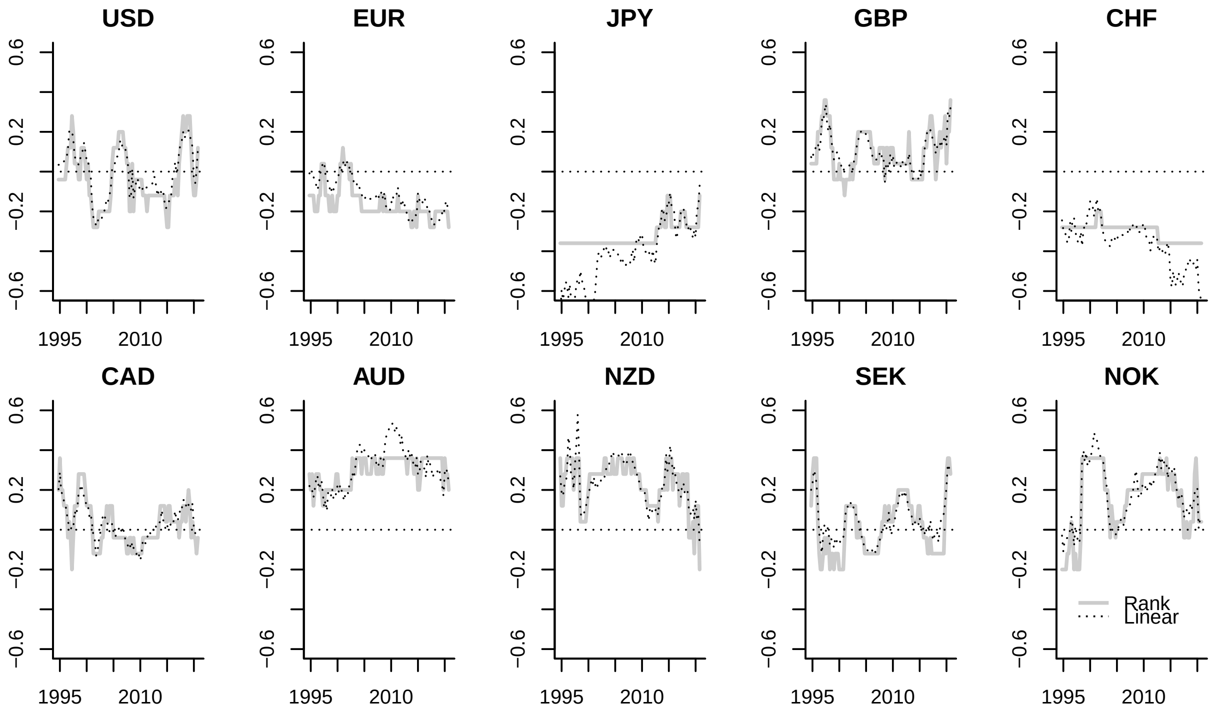
Notes: As in Figure 1.

Figure 4: FX portfolio returns



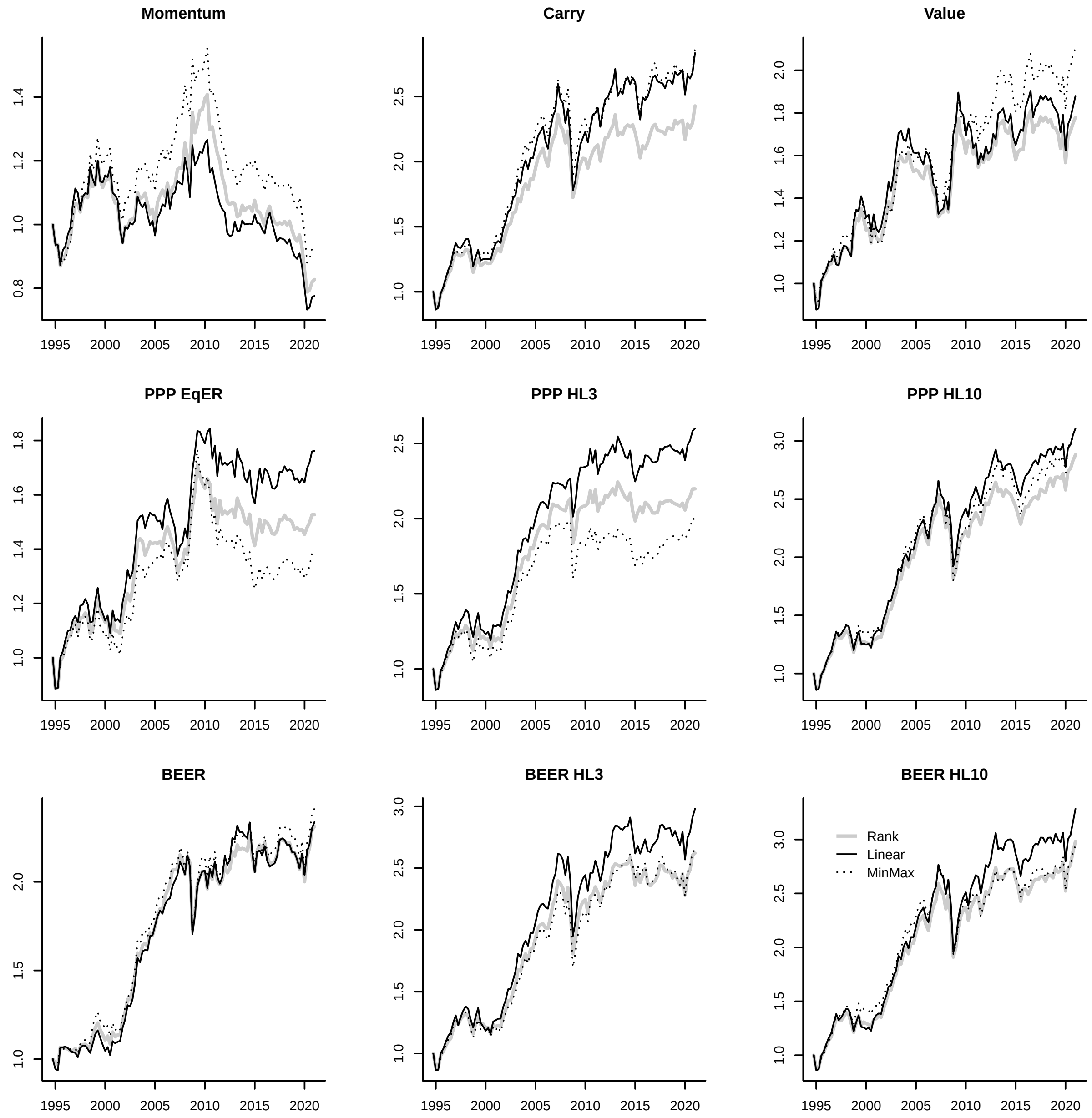
Notes: The upper panels present cumulated rate of returns for $EqER$-based and benchmark strategies. The bottom panels present excess return decomposition into spot rate predictability and forward premium, which is described in equation (4).

Figure 5: Comparison of rank and linear weights



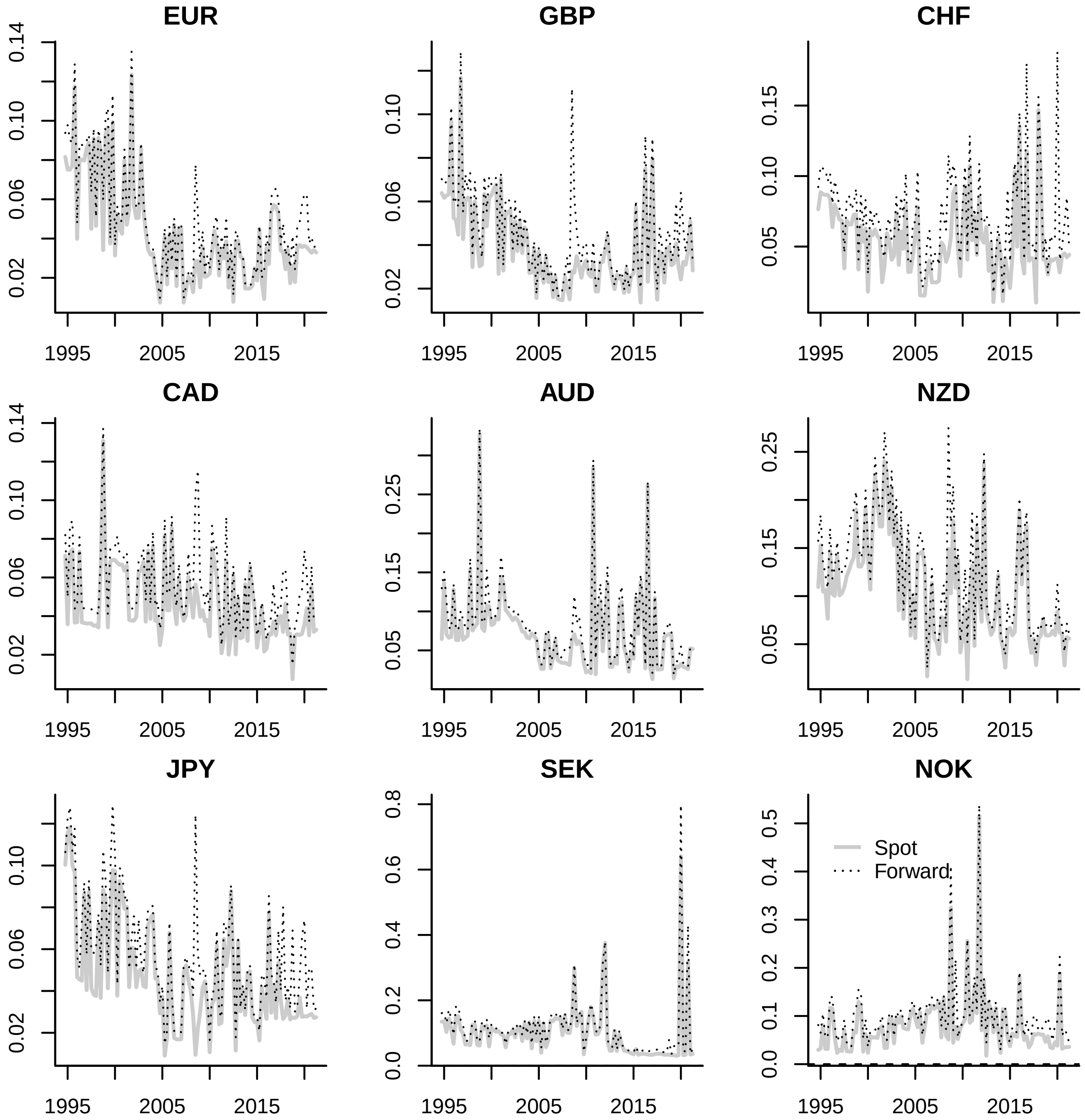
Notes: The figure presents weights of currencies in the $BEER_{HL10}$ portfolio, which are calculated with rank (gray solid line, see equation 8) and linear (black dotted line, see equation 9) methods.

Figure 6: Weighting scheme and FX portfolio returns



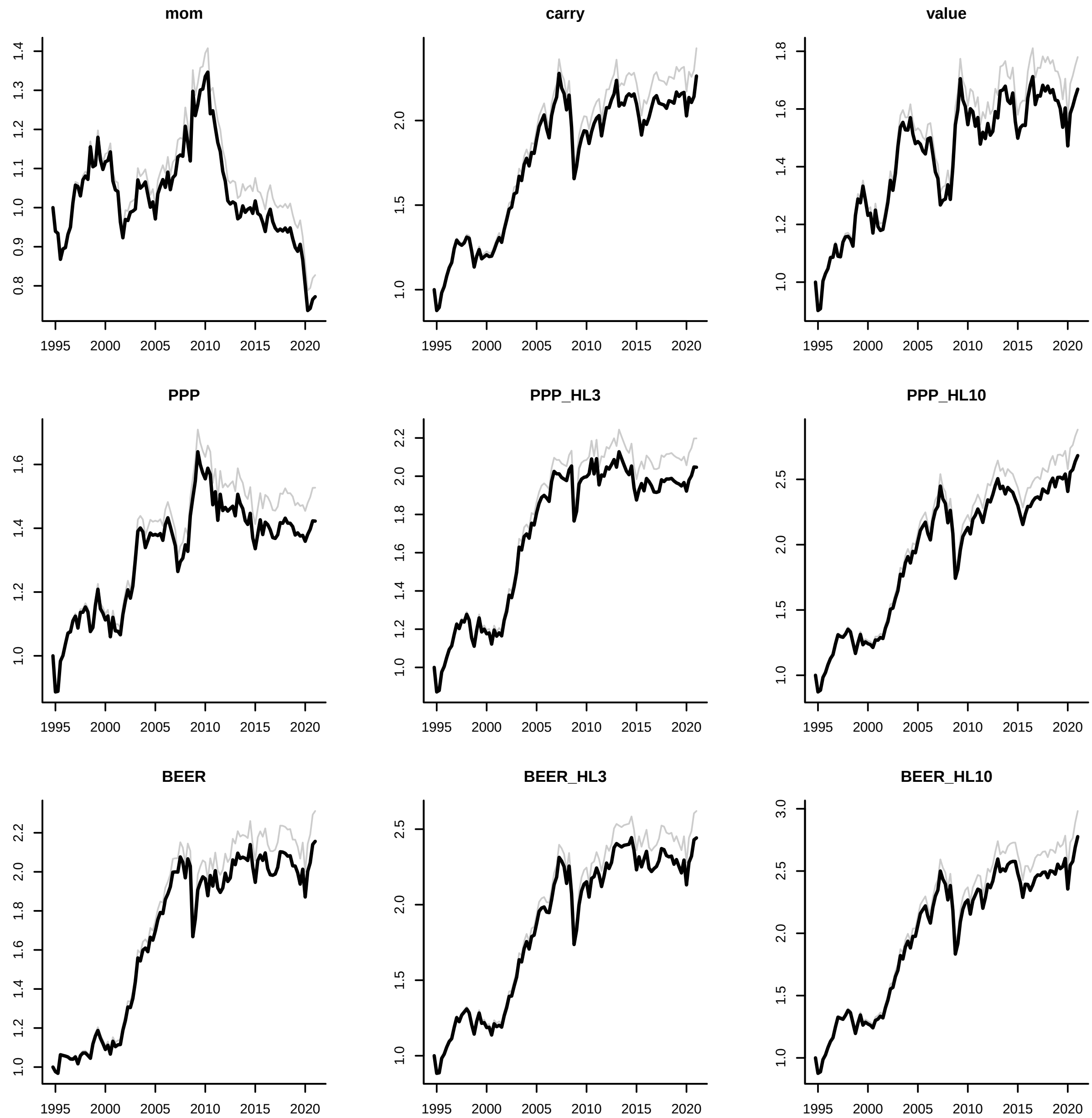
Notes: The figures present cumulated rate of returns for benchmark and $EqER$-based FX portfolios in three weighting scheme variants.

Figure 7: The scale of transaction costs



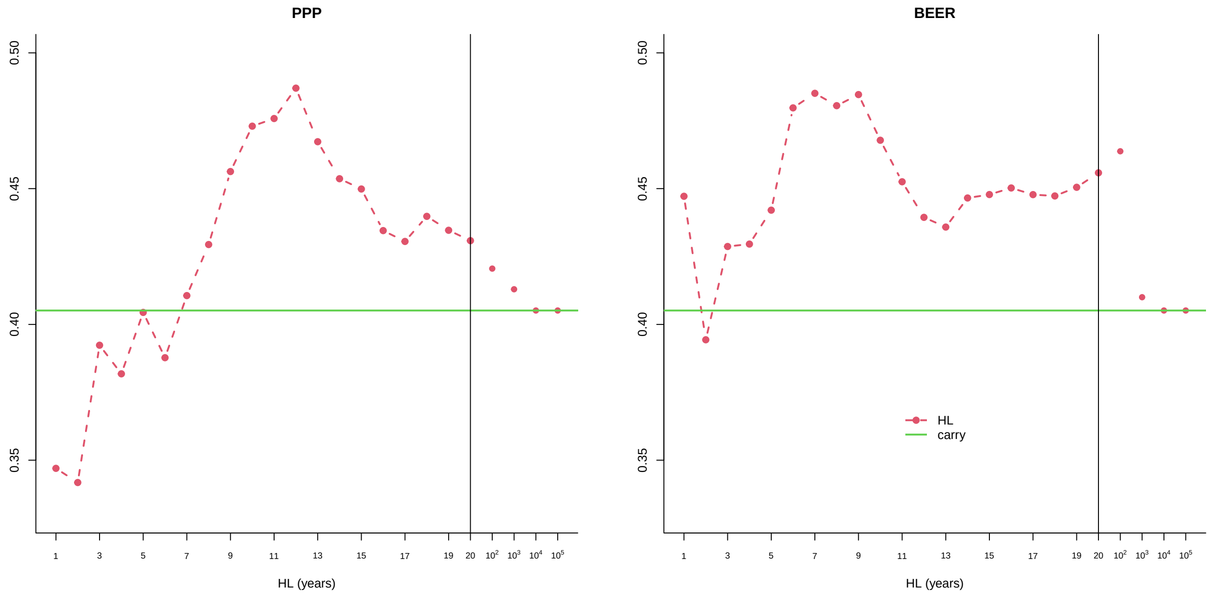
Notes: The figures present the ask-bid spread for spot and forward rate (expressed in %).

Figure 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.

Figure 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 (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.

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Michał Rubaszek
SGH Warsaw School of Economics, Warsaw, Poland; email: mrubas@sgh.waw.pl

Joscha Beckmann
FernUniversität Hagen, Hagen, Germany; Kiel Institute for the World Economy, Kiel, Germany;
email: joscha.beckmann@fernuni-hagen.de

Michele Ca' Zorzi
European Central Bank, Frankfurt am Main, Germany; email: michele.cazorzi@ecb.europa.eu

Marek Kwas
SGH Warsaw School of Economics, Warsaw, Poland; email: mkwas@sgh.waw.pl

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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