# Currency Value*

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**Abstract**

We assess the properties of currency value strategies based on real exchange rates in a cross-sectional setting. We find that real exchange rates have considerable predictive power for the cross-section of currency excess returns. However, adjusting real exchange rates for key country-specific fundamentals – productivity, the quality of export goods, net foreign assets, and output gaps – generates a more refined measure of currency value that is more closely linked to currency risk premia. Accounting for macroeconomic fundamentals considerably enhances the predictive power of currency value measures for currency excess returns.

JEL Classification: F31, G12, G15.

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# 1 Introduction

Determining the intrinsic value of a currency – in short "currency value" – is a key input into decisions by policymakers and global investors.[1] A core building block of any method to determine currency value is Purchasing Power Parity (PPP) and the related concept of the real exchange rate (RER). Real exchange rates embed expectations about future macro fundamentals and currency risk premia, rendering them useful gauges of future currency excess returns. The RER also plays a key role in theoretical and empirical exchange rate models, but the way in which currency valuation measures relate to future currency movements is far from being well understood.

This paper sheds new light on the question of how to measure currency value and how this knowledge can be used to obtain more precise estimates of currency risk premia. We address the following three key questions. Do real exchange rates, as a measure of currency value, predict currency excess returns? If so, can we disentangle information about future fundamentals and future excess returns to obtain a more accurate measure of currency risk premia? And, to what extent do the proposed value measures translate into better investment decisions?

We tackle these questions drawing on a large set of currencies and by means of both panel regressions and currency portfolios. Building portfolios to mimic the returns to a currency value investment strategy allows for a straightforward assessment of the economic significance

[1] In the financial industry, for example, exchange-traded funds that trade currencies using a valuation signal based on real exchange rates are quite common (e.g., the Deutsche Bank Currency Valuation Index). In the policy making community, there is a long history of using models of real exchange rate equilibrium to gauge exchange rate misalignments in central banks and international organizations, notably at the IMF.

of the link between real exchange rates, fundamentals, and currency risk premia.[2]

Our conceptual starting point to study the predictive power of real exchange rates and underlying drivers of currency risk premia is the present-value representation of exchange rates (see, e.g., Engel and West, 2005, 2006; Froot and Ramadorai, 2005). From a present-value perspective, the real exchange rate is driven by i) expected excess returns (currency risk premia), ii) the expected real interest rate differential (RID), and iii), if long-run PPP fails to hold, the long-run expected RER. Hence, adjusting the RER for macroeconomic fundamentals that are related to the latter two expectations should in principle result in a cleaner measure of currency risk premia. It is this basic, yet powerful, idea that we study in this paper in great detail.

The fundamentals we use in the empirical analysis to adjust real exchange rates for movements of expected macro variables are motivated from the international finance literature. We focus on (i) Harrod-Balassa-Samuelson (HBS) effects (measured as real GDP per capita), (ii) the quality of a country's exports, (iii) net foreign assets (a measure of net foreign wealth of a country), and (iv) output gaps. Each of these variables bears a clear link to either long-run expectations of RERs and/or future expected real rate differentials. Most prominently, HBS effects capture the stylized fact that highly productive economies tend to have persistently stronger real exchange rates than less productive ones. Another key variable that should be associated with persistent differences in real exchange rates is the quality of a country's exports. Quality differences (i.e., a departure from the assumption of homogeneous goods) will lead to persistent differences in price levels across countries such that PPP may be vio-

[2]For earlier approaches based on forming currency portfolios see, e.g., Lustig and Verdelhan (2007); Lustig, Roussanov, and Verdelhan (2011); Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011); Menkhoff, Sarno, Schmeling, and Schrimpf (2012a,b); Hassan and Mano (2015); Lettau, Maggiori, and Weber (2014). These papers typically investigate returns to carry trades or closely related portfolios. The focus in this paper is on real exchange rates and related valuation measures which have received much less attention in the recent finance literature – the exceptions being Asness, Moskowitz, and Pedersen (2012); Barroso and Santa-Clara (2014); Kroencke, Schindler, and Schrimpf (2014); Pojarliev and Levich (2010). Heyerdahl-Larsen (2014) calibrates a model with deep habits and consumption bias to match the cross-sectional evidence on portfolios sorted on both carry and value. Balduzzi and Chiang (2014) investigate time-series return predictability of currency returns by real exchange rates, and Engel (2015) investigates the link between RER levels and (real) interest rate differentials in the time-series dimension.

lated over prolonged periods of time. It has also been shown that net foreign assets (NFAs) capture global imbalances that require exchange rate adjustments as part of the mechanism that leads to sustainable current account positions (e.g., Gourinchas and Rey, 2007; Gabaix and Maggiori, 2015). NFAs thus likely play a key role as determinants of currency valuation levels.

Finally, output gaps capture the different states of the business cycle across countries. Given their prominence in the reaction function of central banks (e.g. Engel and West, 2006), output gaps are key indicators of current and expected interest rate differentials across countries. In fact, as we show in this paper, all four macro fundamentals have forecast power for future (real) interest rate differentials. This renders them useful devices to purge the effect of fundamentals from RERs, which in turn helps obtaining a cleaner currency risk premium measure for investment decisions and allows for a better understanding of the information contained in RERs for policymakers.

In our empirical analysis, we start by showing that currency value measures computed from real exchange rates generally serve as a useful input into multi-currency investment strategies. Countries with a weak RER against the U.S. dollar (that is, their currency is cheap in real terms compared to the dollar) have higher currency excess returns going forward than countries with a strong RER. Translating this type of predictability in a currency value investment strategy results in a Sharpe Ratio of about 0.5 p.a. This profitability of simple currency value strategies is in line with what has been reported in earlier work (Asness, Moskowitz, and Pedersen, 2012; Kroencke, Schindler, and Schrimpf, 2014; Barroso and Santa-Clara, 2014).

The key insight of this paper is, however, that standard currency valuation metrics based on real exchange rates need to be adjusted for expectations about future macro fundamentals. Purging the impact of expected fundamentals from the RER delivers a cleaner proxy for currency risk premia. This, in turn, boosts profitability of currency value strategies, generating Sharpe Ratios in the range of about 0.8-0.9 p.a. The rise in Sharpe Ratios largely stems from a lower return volatility of the value strategy. A natural interpretation of this finding is that adjusting the RER for fluctuations in fundamentals (which are not necessarily related to future risk premia) yields a less noisy signal of what constitutes currency value. Currency risk premia will thus be revealed with higher precision.

We conduct further analyses and provide several robustness checks related to our main results. Crucially, we show in a cross-validation exercise that our main results are not driven by a particularly influential currency. Decomposing the information in real exchange rates into its basic components, we find that inflation differentials matter considerably as determinants of currency risk premia. We also explore simple double sorts to show that value and carry strategies are largely independent and thus capture distinct parts of the currency risk premium.[3] Returns of the value strategy accounting for macro fundamentals are not spanned by conventional FX strategies. In fact, the proposed strategy receives a higher weight in the investors' ex-post optimal portfolio allocation than a classical carry strategy. Further, we assess if our results are sensitive to the particular base year used for normalising real exchange rates. We find that this is not the case, as excess returns to value strategies are very similar when using absolute PPP rates (instead of relative ones) for constructing RERs.

Taken together, these results have implications for our general understanding of value in FX markets and currency risk premia in general. Accounting for standard macro fundamentals – well-known in the international finance literature, yet hitherto unexplored in asset pricing work on exchange rates – is highly useful for strengthening the link between currency value and risk premia. Moreover, the findings reported in this paper have implications for asset managers interested in diversifying away from conventional strategies such as carry and momentum or when designing appropriate hedging strategies in a multi-currency context.

Overall, our contributions to the literature are threefold. First, we provide an extensive analysis of currency value strategies in a cross-sectional portfolio setting. This multi-currency

[3] On a related note, see Jorda and Taylor (2012) on how fundamental exchange rate values matter for carry trade returns, and Chong, Jorda, and Taylor (2012) on how HBS effects matter for long-run PPP.

investment approach provides an intuitive measure of the economic value of signals based on real exchange rates and allows us to pin down the basic properties of the returns from value strategies.[4] Our results are obtained in a pure out-of-sample setting, which is important as the vast majority of papers in the literature either do not consider out-of-sample forecasting at all when analyzing real exchange rate models or rely on purely statistical performance measures derived from time-series analysis of a limited number of currency pairs (see, e.g., Rogoff, 1996; Taylor and Taylor, 2004). Second, we shed light on the country-specific macroeconomic fundamentals related to currency value, allowing to better identify cross-country variation in risk premia. This is particularly important given the work of Hassan and Mano (2015), suggesting that that currency risk premia are mostly static. Isolating their ultimate macro drivers is therefore key towards a better understanding of currency markets. Third, while we find that simple PPP calculations only provide a very crude measure of currency value in our broad cross-section of currencies, we show how adjusting real exchange rates for macro fundamentals delivers a more accurate measure of currency value that displays stronger predictive power for future currency returns.

The paper proceeds as follows. To set the stage, Section 2 lays out the framework for thinking about real exchange rates, macro fundamentals and currency risk premia. This serves as guidance for our empirical work throughout the paper. Section 3 then presents the data. In Section 4 we investigate the predictive power of real exchange rates for excess returns. In particular, we show how accounting for fundamentals affects this forecast power. Section 5 provides additional results and robustness. Section 6 concludes.

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[4]See Melvin and Shand (2013) on the relevance of cross-sectional (as opposed to time-series) predictability for actual implementations of currency strategies.

# 2 A framework for measuring currency value

## 2.1 Definition of real exchange rates

The RER, $Q$ is the most common measure of currency valuation and forms the basis of our analysis. We work with the following definition

$$Q_t = \frac{P_t}{S_t P_t^\star}, \tag{1}$$

where $S$ denotes the exchange rate change (USD per unit of foreign currency), $P$ denotes the U.S. price level, and $P^\star$ denotes the foreign price level. Real exchange rates that differ from unity thus capture the deviation of a currency's value from PPP (see, e.g., Rogoff, 1996; Taylor and Taylor, 2004). The definition of RER here is such that a higher RER ($Q$) means a stronger dollar and, consequently, a *lower* valuation level of the foreign currency. The log real exchange rate is $q_t = p_t - p_t^\star - s_t$, where lowercase letters denote logs of variables. Note that the nominal spot exchange rate, $S$, is defined in the opposite way, i.e., a higher value of $S$ means that the foreign currency is more expensive (stronger) in nominal terms. We do so to simplify the presentation of results in the subsequent empirical analysis.

## 2.2 A present-value perspective on real exchange rates

To motivate our empirical approach we draw on the standard present-value formulation of real exchange rates (e.g. Engel and West, 2005; Froot and Ramadorai, 2005). By definition, the currency excess return, $rx$, is given by

$$rx_{t+1} = -(q_{t+1} - q_t) + (ri_{t+1}^\star - ri_{t+1}), \tag{2}$$

where $ri$ is the real interest rate (Froot and Ramadorai, 2005). Rewriting this equation as

$$q_t = rx_{t+1} - (ri^{\star}_{t+1} - ri_{t+1}) + q_{t+1}, \tag{3}$$

and then taking conditional expectations and iterating forward gives

$$q_t = \sum_{h=1}^{\infty} E_t\left[rx_{t+h}\right] - E_t\left[ri^{*}_{t+h-1} - ri_{t+h-1}\right] + E_t[q_{t+\infty}]. \tag{4}$$

Hence, the RER is driven by three terms: expected excess returns (risk premia), expected real interest rate differentials, and the long-run expected real exchange rate. It is standard to impose $\lim_{h\to\infty} q_{t+h} = 0$, i.e., the RER level equals unity in expectation in the very long run (consistent with PPP). The assumption of a unitary real exchange rate in the very long-run is not innocuous, however. It is well documented that there are structural and persistent differences between countries, such that even in the long-run there can be significant violations of the standard PPP condition (e.g. Rogoff, 1996; Taylor and Taylor, 2004).

Importantly, Equation (4) suggests that the relation of interest between the RER and (expected) currency risk premia will also be influenced by macroeconomic fundamentals as these are the forces ultimately driving (expectations of) future real rate differentials. To sharpen the relation between the RER and risk premia, we thus aim at controlling for such influences. In turn, one would expect that the signal from the RER for risk premia becomes more precise and that a trading strategy built on such a signal will be more profitable. This is the central hypothesis we take to the data in this paper.

A key question is what macroeconomic fundamentals can be expected to influence expectations of future real rate differentials as well as the long-run mean of the real exchange rate when PPP deviations are very persistent. We consider four fundamentals in this paper: i) productivity, to capture Harrod-Balassa-Samuelson (HBS) effects, ii) the quality of a country's exports, iii) net foreign assets (NFA), and iv) the output gap. We provide a brief discussion of each of these macroeconomic drivers next.

**Harrod-Balassa-Samuelson effects.** The definition of $Q$ given above is derived from the law of one price applied to prices of individual goods that are perfectly substitutable and internationally tradable. Relaxing the assumption that all goods in the price indices $P$ and $P^*$ are tradable (as is the case, for example, for a consumer price index) gives rise to HBS effects. More productive economies tend to experience stronger real exchange rates. The key mechanism is that wages in the non-tradable sector tend to follow wages in the tradable sector. Thus, high productivity countries have higher overall price levels and, hence, stronger real exchange rates as price differences in the non-tradable sector cannot be eliminated by goods market arbitrage.

**Exports quality.** Relaxing the assumption of perfect substitutability – for example due to differences in the quality of a country's traded goods – introduces a wedge in price levels. Countries producing higher-quality goods experience stronger real exchange rates. An example for the relevance of exports quality is manufactured goods in Switzerland (e.g. watches).

**Global imbalances.** Global imbalances in asset positions may impact the RER via various channels. In a world with financial frictions, the financing of capital flows associated with imbalances in international asset positions may give rise to a risk premium embedded in currency valuation levels (Gabaix and Maggiori, 2015). The indebted economy which has to pay this premium can ease its burden by a tentatively undervalued exchange rate, i.e. a lower valuation level of the respective currency. Following our definition this means having a higher $Q$. Also, a vast literature on the relationship between international payments and real exchange rates argues that there is a long-run comovement between net foreign assets and real exchange rates and that countries with net external liabilities have more depreciated real exchange rates, with the main channel of transmission operating through the relative price of nontraded goods (e.g., Lane and Milesi-Ferretti, 2004). This literature also shows that there is a cross-sectional correlation between real interest rates and net foreign asset positions (e.g., Rose, 2010). Therefore, net foreign assets can potentially impact the RER through various mechanisms.

**Output gaps.** Finally, output gaps are primary candidates as drivers of real exchange rates due to their prominence in the central bank's reaction function. Engel and West (2006) set up a decomposition of the RER that incorporates a link to fundamentals underlying the monetary policy decision of central banks.[5] Specifically, they posit that central banks in the home and foreign country follow a Taylor (1993) rule, thereby linking the RER to expectations about future output gaps (via the interest rate channel in Eq. (4) above). Therefore, we incorporate output gaps in the empirical analysis below.

Overall, there are good reasons to believe that these macroeconomic factors are related to future real interest rate differentials and/or the expected level of the RER (in the case when the transversality condition fails to hold). Controlling for these variables should therefore lead to a measure of the currency valuation that is more closely tied to currency risk premia.

# 3 Data

## 3.1 Exchange rates

Our exchange rate data are taken from the Global Financial Database (GFD) and cover a long sample period from 1970Q1 to 2014Q1 at the quarterly frequency. Exchange rates are end-of-quarter values. The empirical analysis is based on exchange rate changes and returns starting in the first quarter of 1976, i.e. shortly after the fall of Bretton Woods.[6]

Our RER measure is based on real exchange rates normalized to unity in 1970Q1 for all countries. We can proceed this way as we have a balanced sample of consumer price inflation

[5]Taylor-rule fundamentals have been found to be accurate predictors of bilateral exchange rates in the macro exchange rate literature (e.g. Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2008; Molodtsova and Papell, 2009).

[6]We use the earlier years from 1970 to 1975 to compute long-run growth rates of various macro variables and RER changes to ensure that the empirical analysis can start in the first quarter of 1976.

indices (CPI) – also obtained from the GFD – and exchange rates spanning the entire sample period for all countries. However, these real exchange rates are based on relative PPP rates, which means there is a base-year effect. We deal with this in two ways. First, most of the empirical analysis in this paper will use five-year changes in the RER as a value signal (as in, e.g., Asness, Moskowitz, and Pedersen, 2012), and therefore this base effect does not matter. Second, we show in the robustness section that RERs computed from absolute PPP yield similar results.[7]

We collect data on a cross-section of 23 developed and emerging countries. Since all exchange rates are quoted against USD, we have a total of 22 exchange rates. The sample covers Australia, Canada, France, Germany, Hungary, India, Indonesia, Italy, Japan, South Korea, Mexico, New Zealand, Norway, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom and the United States. We eliminate France, Italy, and Spain from the sample in 1999 after they adopted the Euro, only keeping Germany in the sample.

**Macro fundamentals.** In addition to spot rate data and CPI indices we also obtain data on additional (macro) variables for the same set of countries, retrieved from the GFD. These data include short-term (3-month) interest rate (T-bills), nominal GDP, population and net foreign asset positions. Data on macro variables are not available for all countries and/or at each point in time in the GFD, and hence we are dealing with an unbalanced panel whenever we include these macro fundamentals in our analysis.

We employ data on nominal GDP, CPI indices and population figures to construct real per capita GDP measures for all countries. These are needed to approximate the magnitude of HBS effects. We also use real GDP to compute output gap (OG) measures. We estimate

[7] These data, obtained from the OECD, are available for a slightly smaller cross-section of countries and PPP rates are only available at the annual frequency but the results reported below are qualitatively robust to using this absolute PPP measure. We choose to work with GFD-based PPP rates in our main analysis because of the larger cross-section, higher frequency, and because the OECD PPP rates were first constructed in the 1990s and would not have been available in the 1970s (the start of our sample).

these output gaps as deviations from quadratic trend regressions (see, e.g., Clarida, Gali, and Gertler, 2000; Cooper and Priestley, 2009). We run these regressions separately for each country and on a recursively expanding window, allowing for an initialization window from 1970Q1 to 1975Q4.

Data on the quality of export goods are taken from the International Monetary Fund (IMF). These data are discussed separately in the next section as they have not been used extensively in earlier research. Data on net foreign assets (NFA) are taken from Lane and Milesi-Ferretti (2007) and the time series of NFA positions is updated until 2014 as in Della Corte, Riddiough, and Sarno (2015). Finally, we compute (ex-post) real interest rates (and real interest rate differentials against the USD, denoted as RID) by subtracting CPI inflation from nominal 3-month interest rates.

### 3.2 Measuring the quality of export goods

As outlined above in our core analysis, the fair value RER approach relies on adjustments for country-specific fundamentals, most of which are fairly common in the literature and for which data are easily available. However, the measurement of the quality of exports deserves further discussion. We use an export quality index constructed by the IMF and described in detail by Henn, Papageorgiou, and Spatafora (2013). The basis for the index construction is an extension of the UN-NBER dataset covering bilateral trade at the SITC 4-digit level. The quality index of export goods is constructed bottom up from a very disaggregated level of 851 product categories. The idea is to adjust unit values for differences in production costs and a selection bias coming from the relative distance between exporter and importer. At the end of this process there are about 20 million quality estimates, each covering a specific exporter-importer-product combination. These estimates are then aggregated in a final step into a country index of export quality.

The export quality data constructed by the IMF are a substantial improvement relative to the most common proxy for export quality used in prior literature, which tends to employ unit values (that is, the average trade prices for each product category). Indeed, it is well known that unit values are a noisy proxy for export quality since they are affected by a series of other factors, including production cost differences (e.g., Hummels and Klenow, 2005). There are a few studies in the literature that construct data for export quality that mitigate these issues, typically by employing structural models that specify demand (and sometimes supply) for traded goods with explicit microfoundations; an example of this literature is the work carried out in Vandenbussche (2014) for the European Commission, as well as the literature surveyed therein. That said, these studies do not provide a sample of sufficient size (both time-series and cross-sectional) for the kind of analysis in this paper. Hence, a rigorous robustness analysis using an alternative dataset of similar quality to the IMF data is not possible. However, we were able to obtain the data on export quality generated by Vandenbussche (2014), which are based on a structural model with identifiable quality parameters. These data only cover a short period from 2005 to 2010 and a subset of our cross-section of countries.[8] While it is not possible to run regressions or build portfolios with a dataset of this size, we checked the correlation of this quality indicator with the IMF data for the overlapping sample of countries. The cross-sectional correlation of these data with the IMF export quality data is: 0.71 (in 2005), 0.49 (in 2006), 0.72 (in 2007), 0.77 (in 2008), 0.82 (in 2009), and 0.74 (in 2010). Overall, these correlations seem fairly high and suggest that the ranking implied in a portfolio sorting procedure would be very similar, meaning that the IMF export quality data appear to be consistent with the quality measures derived from a fully-fledged structural model.[9]

For our analysis below, we construct (log) export quality differentials (against the U.S.) and set the relative quality to a value of zero in 1970 in the same way as for our CPI-based

[8] There six countries in our sample for which he have quality data from the IMF and from Vandenbussche: Eurozone (Germany), Hungary, Japan, Sweden, United Kingdom, United States. In addition, we have data in both data sets for France, Italy, and Spain but these countries are not included in our sample after the introduction of the Euro.

[9] We are grateful to Hylke Vandenbussche for graciously sharing her export quality data.

(log) real exchange rates, so that the two measures are comparable.

**Currency returns.** We are interested in the returns to value strategies and currency risk premia and, hence, we compute currency excess returns as

$$RX_{t+1} = \frac{S_{t+1}}{S_t}\frac{(1+i_t^*)}{(1+i_t)},$$

where $S_t$ denotes the nominal exchange rate at the end of quarter $t$, $i_t^*$ denotes the end-of-quarter foreign interest rate, and $i_t$ denotes the end-of-quarter U.S. interest rate. The excess return measures the return accruing to a U.S. investor who borrows at the US interest rate $i$ and uses the funds to hold a position in foreign currency for one quarter, earning the foreign interest rate $i^*$ and then converting the proceeds back to dollars.

Later in the paper, we also compare the results for currency excess returns to those of simple currency returns, or exchange rate changes, which just represent the spot rate component of the currency excess return (i.e., $\Delta S_{t+1} = S_{t+1}/S_t - 1$). While excess returns tell us about the overall return of a U.S. investor trading in foreign currencies, the exchange rate change isolates the return contribution from changes in the asset price itself, i.e., the change in the spot exchange rate. Note that our definition of nominal spot exchange rates (USD/FC) means that a positive $\Delta S_{t+1}$ implies an appreciation of the foreign currency. Likewise, a positive $RX$ indicates a positive excess return to holding foreign currency for a U.S. investor.

Table 1 reports descriptive statistics for returns and real exchange rates (and the components of real exchange rates, spot rates and inflation differentials). Specifically, we report means and volatilities for excess returns, spot exchange rate changes, real exchange rates, real exchange rate changes, and inflation differences in our sample. Average returns and exchange rate changes – as well as their volatilities – are annualized.

– Table 1 about here –

Table 1 shows there is strong variation across countries, not just when it comes to average currency excess returns, but also when looking at classical currency valuation metrics or macro variables such as inflation.

# 4 Real exchange rates and currency risk premia

## 4.1 Macroeconomic fundamentals and real interest rate differentials

As is clear from the decomposition in Eq. (4) above, real exchange rates are driven by i) expected excess returns (currency risk premia), ii) expected real intererest rate differentials (RIDs), and iii) the long-run expected RER if long-run PPP fails to hold. Hence, adjusting the RER for macro fundamentals that are related to the latter two expectations should result in a cleaner measure of currency risk premia.

As a preliminary exercise to investigate whether and which fundamentals affect the RER, we run simple Granger causality-type tests to assess whether the macro fundamentals discussed above relate to future RIDs. We do so by regressing RIDs on lagged macro fundamentals (and lagged RIDs) in a panel regression with time fixed effects. This specification ensures that we investigate the cross-sectional dimension, which is consistent with the construction of value portfolios later in the paper. Inference is based on two-way clustered standard errors (clustered by currency and quarter). We present p-values for the null hypothesis of no predictability for forecast horizons of $1, 2, ..., 5$ years in Table 2.

The results suggest that all macro fundamentals considered have some predictive power for future RIDs. This renders them useful as control variables when purging expected fundamentals from RERs to better isolate a value signal. Interestingly, the macro fundamentals differ in terms of the horizon over which they predict real exchange rates. For example, NFA positions are the best predictor at short forecast horizons, whereas output gaps work best at intermediate horizons. Judged from the strength of the statistical relationship, export quality emerges as the strongest driver of real rate differentials at all horizons.

– Table 2 about here –

### 4.2 Accounting for macro fundamentals to better predict excess returns

Next, we go beyond the direct relation of macro fundamentals to RIDs and examine the effects of both on currency excess returns. Specifically, we run panel regressions with time fixed effects of excess returns on (one quarter) lagged RER and macro fundamentals

$$RX_{i,t+1} = \alpha + \beta RER_{i,t} + \gamma X_{i,t} + \tau_{t+1} + u_{i,t+1} \tag{5}$$

where $\beta$ denotes the predictive slope of the RER, $X$ are control variables, and $\tau$ is a time fixed effect. We employ two-way clustered standard errors as above (clustered by currency and time). Table 3 presents results for different specifications of this regression. As noted above, our measure of the RER in this exercise follows the literature and is based on the 5-year change in the RER level as in, e.g., Asness, Moskowitz, and Pedersen (2012).

We start with results for a benchmark case where we only include the RER and no controls, reported in Panel A, specification (i). We find a statistically significant slope coefficient for lagged RER of 0.027 with a $t$-statistic of 3.24. These baseline results corroborate the usefulness of simple currency value measures based on the RER for predicting currencies.

In the next step, we consider additional variables to the regression to sharpen the predictions by the currency value signal. Specification (ii) adds lagged RIDs as a control, which only has a marginal effect on the slope coefficient for the RER, however. Specifications (iii) - (vi) add different (lagged) macroeconomic fundamentals (one at a time) to the regression, while always controlling for RID as well. We find that the slope coefficient on lagged RER increases in all cases and that statistical significance becomes stronger as well. This effect is especially pronounced in specification (vii) where we include all lagged macro fundamentals jointly. The slope coefficient increases to 0.039, more than 40% higher than in the benchmark regression, and the $t$-statistic of the RER increases to 4.46. Hence, controlling for macro fundamentals enhances the predictive power of RER for future excess returns. Panel B of Table 3 shows very similar results when excluding RID from all regressions. Hence, these results are not driven by controlling for carry in particular.

– Table 3 about here –

We also run regressions of future excess returns on lagged 5-year changes in RER, lagged fundamentals, and lagged returns

$$RX_{i,t+h} = \alpha_h + \beta_h RER_{i,t} + \gamma_h X_{i,t} + \delta_h RX_{i,t} + \tau_{t+h} + u_{i,t+h} \tag{6}$$

for forecast horizons of $h = 1, 2, ..., 20$ quarters. The sequence of estimated $\beta_h$ coefficients can be thought of as the impulse-response function of excess returns to changes in the RER while holding the path of macro fundamentals constant – a method known as local projections (see Jorda, 2005). Results for a specification where we do not include controls ($\gamma = 0$) is shown in the upper part of Figure 1 whereas the lower part of that figure shows results for the case where controls are included. In both cases, we plot the sequence of estimated $\beta_h$ coefficients and 95% confidence intervals based on two-way clustered standard errors.

– Figure 1 about here –

Similar to the results in Table 3 discussed above, we find that return predictability by the 5-year RER change strengthens when controlling for macro fundamentals. The predictive coefficient is higher at all horizons $h$, and predictability is much more persistent and extends to about two years when controlling for fundamentals. By contrast, when fundamentals are not controlled for the horizon over which currency value predicts returns is only one year.

Next, we test the above relations in a portfolio setting which directly allows implementing trading strategies and inferring their economic value.

## 4.3 Currency value strategies

### 4.3.1 Constructing currency value portfolios

In our benchmark setup, we build currency portfolios based on linear weights given by

$$w_{j,t+1} = c_t \left( x_{j,t} - \overline{x}_t \right), \tag{7}$$

where $x_{j,t}$ denotes the signal for currency $j$ in quarter $t$ (such as the RER) and $\overline{x}_t = N_t^{-1} \Sigma_{j=1}^{N_t} x_{j,t}$ denotes the *cross-sectional average* of this signal (across countries, $N_t$). $c_t$ is a scaling factor such that the absolute sum of all portfolio weights equals unity. Currencies with a value of the signal above the cross-sectional mean receive positive portfolio weights, whereas currencies with a below-average value receive negative portfolio weights. The portfolio return $rx^p$ is then given by $rx_{t+1}^p = \sum_{j=1}^{N_t} w_{j,t+1} rx_{j,t+1}$. In the implementation of this approach we re-balance the portfolios at the end of each quarter.

This setup where weights are linear in the signal is simple but very useful for decomposing the overall portfolio return into different components of the signal. For example, suppose we can decompose a signal $x_{j,t}$ into two components such that $x_{j,t} = x_{1,j,t} + x_{2,j,t}$; then the returns to the two portfolios based on $w_{1,j,t+1} = c_t(x_{1,j,t} - \overline{x}_{1,t})$ and $w_{2,j,t+1} = c_t(x_{2,j,t} - \overline{x}_{2,t})$ will add up to the overall portfolio return based on the composite signal $x_{j,t}$ defined above. This allows us to perform simple decompositions of the predictive information in currency value into different underlying drivers (e.g., changes in spot rates vs inflation).

In addition to the benchmark portfolio results based on linear weights, we also report returns of rank portfolios (see,e.g. Asness, Moskowitz, and Pedersen, 2012; Koijen, Moskowitz, Pedersen, and Vrugt, 2013), where weights are given by

$$w_{j,t+1} = c_t \left( \text{rank}(x_{j,t}) - \sum_{j=1}^{N_t} \text{rank}(x_{j,t})/N_t \right). \tag{8}$$

The scaling factor $c_t$ is analogous to the case of linear portfolio weights above and ensures that portfolio weights sum to one in absolute value. This procedure is more conservative (in that outliers and other extreme scores of signals receive a smaller weight), but the downside is that it does not permit exact decompositions.

Finally, we also perform standard cross-sectional portfolio sorts for comparison, sorting currencies into four bins ($P_1, P_2, P_3, P_4$) based on quartiles of the cross-sectional distribution of real exchange rates. Within each bin, currencies are equally weighted (as, e.g., in Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a). We report results for a high-minus-low portfolio ($HML$) which is long in $P_4$ (weak real exchange rates) and short in $P_1$ (strong real exchange rates).

### 4.3.2 Benchmark results

We start by building benchmark value portfolios drawing on the same measure as above, i.e. the 5-year change in the RER. We build value portfolios based on 4 portfolios ($P_1$, ..., $P_4$) and a high minus low (HML) portfolio. We also build rank portfolios and portfolios based on linear weights as explained above. Results are shown in Table 4.

– Table 4 about here –

We find that standard value portfolios deliver statistically significant positive excess returns which also seem economically significant. Sharpe Ratios range between 0.44 and 0.51

and hence are of similar magnitude as in Asness, Moskowitz, and Pedersen (2012).

#### 4.3.3 Currency value strategies accounting for macroeconomic fundamentals

We then report results for modified value strategies in Table 5 where we purge the RER of macro fundamentals based on the intuition in Eq. (4). We do so by using four different procedures to adjust the value signal for fundamentals. First, we simply regress 5-year RER changes on macro fundamentals in the cross-section in each quarter. We save the fitted value (denoted $\widehat{Q}$ in Table 5) and the residual (denoted $\varepsilon^{Q}$) for each quarter, and build linear and rank portfolios based on this decomposition of the value signal. Panel A of Table 5 refers to this case. Second, we use exponentially weighted moving averages of all fundamentals to proxy for expected fundamentals (Panel B). We then run cross-sectional regressions of the value signal on these proxies for expected fundamentals and, again, sort currencies into portfolios based on either the fitted value or the residual.[10] The third case, in Panel C, uses a simple VAR of all fundamentals to compute expected fundamentals. We estimate VARs separately for each country and recursively based on an initialization window from 1970Q1 to 1975Q4. Expected fundamentals are then based on iterating the VAR forward (and truncating after 20 quarters). Finally, Panel D shows results for a setup where we estimate a panel VAR for all countries jointly. Apart from this the procedure is the same as for the individual country VARs discussed above.

Table 5 shows annualized mean returns, $t$-statistics based on Newey and West (1987) standard errors, return volatilities, and Sharpe Ratios for linear (left) and rank (right) portfolios,

[10] We approximate expectations as discounted long-run growth rates of some macro fundamental as $\widetilde{g}_t = \left(\sum_{j=0}^{\infty} \phi^j g_{t-j}\right) / \sum_{j=0}^{\infty} \phi^j$, and then use $\widetilde{g}_t$ as a proxy for investors' long-run expectations about the fundamental $g$. This approach to proxying for expectations has been used in earlier work on U.S. inflation expectations (e.g., Piazzesi and Schneider, 2011; Cieslak and Povala, 2015) and draws on insights from the adaptive learning literature (Evans and Honkapohja, 2009). In adaptive learning, agents learn recursively as soon as new data becomes available; $1 - \phi$ is the gain parameter. Kozicki and Tinsley (2005) find that long-run weighted averages for U.S. inflation match survey inflation expectations for the U.S. quite well. For our setup based on quarterly data, we follow Piazzesi and Schneider (2011) and set $\phi = 0.98$. We truncate the sum at 20 quarters.

and for a portfolio based on the 5-year change in the RER ("RER"), the fitted signal ($\widehat{Q}$), and the residual signal ($\varepsilon^Q$). We always report returns for the benchmark value signal ("RER") for comparison since including macro variables in different ways changes the available sample period.

– Table 5 about here –

For all four cases in Panels A – D, we find that adjusting the RER for macro fundamentals increases the Sharpe Ratio substantially. This effect is not driven by higher mean returns but rather by lowering return volatilities. This can also be seen clearly from plots of cumulative returns in Figure 2. Hence, purging the value signal of (expected) fundamentals results in a cleaner measure of risk premia, consistent with the intuition developed in Section 2.2.

– Figure 2 about here –

This effect also translates into other measures of risk which also tend to improve when adjusting for macroeconomic fundamentals. For example, we plot the drawdown dynamics of standard value portfolios ("RER") and modified value portfolios ($\varepsilon^Q$). We employ returns based on the panel VAR specification in Panel D of Table 5 in Figure 3. This figure clearly shows that adjusting for fundamentals reduces downside risk of the currency value strategy substantially.

– Figure 3 about here –

#### 4.3.4 Exposure to other currency risk factors

Next, we explore how the value strategies relate to other currency risk factors. To do so we run regressions of value returns adjusted for expected fundamentals (based on the panel VAR in Panel D of Table 5) on returns to carry, momentum, standard value (based on 5-year

RER changes), and the global imbalance (IMB) factor of Della Corte, Riddiough, and Sarno (2015). The latter is available from 1983Q4 onwards only, so we run separate regressions with this factor. Results are shown in Panel A of Table 6.

– Table 6 about here –

We find that the modified value strategy ($\varepsilon^Q$) that strips value signals from expected macro fundamentals delivers significant alphas across all specifications and even when including standard value returns in the regression (specifications (iii) and (vi)). Information ratios are quite high, ranging from 0.53 to 0.91 (annualized). Finally, Panel B of Table 6 shows weights of the different strategies in the tangency portfolio. The modified value strategy gets a large and significant weights in all specifications. It even exceeds that of a classical carry strategy, which has received most of the focus in the leiterature so far[11]

# 5 Additional results and robustness

## 5.1 Macro fundamentals and real exchange rates in the cross section

To further understand the link between our macro fundamentals and value signals, we run panel regressions of 5-year RER changes on our set of macro fundamentals. We include time fixed effects and inference is based on two-way clustered standard errors (clustered by currency and quarter). Table 7 shows that higher productivity (HBS), higher export quality, higher net foreign assets, and larger output gaps are associated with stronger real exchange rates (i.e. a lower RER in our notation). Except for NFA, all fundamentals enter significantly

[11] The weights are calculated for an ex post tangency portfolio to show that that ex post efficient frontier would include the modified value strategy, with a large weight. This result does not necessarily imply an expansion of the ex ante frontier but, given the large weight attributed to the value signal, this possibility seems unlikely.

in either the univariate regression or the multivariate specification or both.[12]

However, the $R^2$ is at most 33% (for specification (ii)), so a substantial share of the cross-sectional dispersion in value signals is left unexplained. Our results above suggest that this unexplained part is largely driven by expected excess returns (currency risk premia).

– Table 7 about here –

### 5.2 Decomposing value signals

We decompose the RER level into several components to further understand the drivers of return predictability. Specifically, we first split the information in the RER level ($q_t$) into that in the lagged 5-year RER level ($q_{t-5y}$) and the 5-year change in the RER ($\Delta q_{t-5y;t}$), the latter being the standard value signal in the literature.[13] With this basic decomposition at hand, we then split the information content of 5-year RER changes into the parts attributable to the (negative) 5-year spot rate change ($\Delta s_{t-5y;t}$) and (negative) 5-year inflation differential ($\Delta \pi^*_{t-5y;t}$), respectively. This decomposition tells us whether lagged RER levels or changes drive return predictability and whether return predictability by the 5-year RER change stems from the spot rate component or inflation differentials. We build linear portfolios which allow for an exact decomposition of returns and rank portfolios for robustness. Results are presented in Table 8.

– Table 8 about here –

Results based on the exact decomposition with linear portfolio weights in Panel A show that around 60% of the excess return predictability of the RER level comes from 5-year

[12]Note that we are using the value signal here, i.e., the 5-year changes of RER, for consistency with our empirical test above. Using the RER level instead, we find that a more positive international investment position (higher NFA) is associated with a higher valuation level as predicted by theory.

[13]This decomposition is akin to work in the equity market literature (e.g., Gerakos and Linnainmaa, 2015), aimed at decomposing the information content of book-to-market ratios for equity returns.

changes in the RER, i.e., the standard value signal in this paper and the literature (Asness, Moskowitz, and Pedersen, 2012; Barroso and Santa-Clara, 2014; Kroencke, Schindler, and Schrimpf, 2014). The remainder comes from the 5-year lagged level (which is not statistically significant though). Hence, using 5-year RER changes seems to capture the predictive power of RER for currency returns well. Furthermore, we find that lagged inflation differentials and lagged 5-year spot exchange rate changes have opposite predictive power for currency returns. Going long the currencies of countries with high inflation (relative to the U.S.) forecasts positive excess returns relative to low inflation countries. This suggests there might be a risk premium for high inflation countries. For the spot rate component, we find that going long countries with high 5-year appreciation rates forecasts low excess returns relative to currencies which depreciated over the last 5 years. Hence, strong currencies tend to earn low risk premia going forward.

### 5.3 Carry and value: Sequential sorts

A standard benchmark strategy in currency markets is the carry trade, which goes long currencies with high interest rates and short currencies which offer low interest rates (see, e.g., Lustig and Verdelhan, 2007; Brunnermeier, Nagel, and Pedersen, 2009; Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011). To better understand the link between carry and value, we form sequential portfolios where we first, in each quarter, split the set of available currencies into two baskets (along the median value) according to one signal. Then, we form rank portfolios within these two baskets based on a second signal.

Table 9 reports results for this exercise. The left part of the table reports returns to value portfolios built within buckets of currencies with high or low carry whereas the right part of the table refers to carry portfolios built within baskets of currencies with high or low value.

– Table 9 about here –

The results suggest that, judging from the Sharpe Ratio, carry strategies tend to perform better among currencies with high value (i.e., low valuation). Value strategies, by contrast, work better among low carry currencies. The differences in Sharpe Ratios are not very large in economic terms, though. A reasonable conclusion seems to be that value and carry capture largely unrelated dimensions of currency risk premia.

### 5.4 Home bias and real exchange rates

Another factor that should be related to real exchange rates (e.g. Warnock, 2003) is home bias in trade. The intuition for this link is that countries with stronger home bias have a stronger preference for domestic goods. Stronger home bias then becomes a friction that prevents PPP from holding and, in particular, leads to higher price levels in the country with stronger home bias. Hence, one should observe stronger RER for countries with stronger home bias in goods markets.

We tackle this question by means of two different measures of home bias: (i) home bias in trade and, for robustness, (ii) home bias in equity investments.[14] To measure home bias in trade, we simply rely on import shares (imports divided by nominal GDP) as in Heathcote and Perri (2013). These data are available from the GFD as well. Home bias in equity investments is measured via the IMF's Coordinated Portfolio Investment Survey (CPIS). The main idea of the asset market home-bias measure is to relate a country's foreign asset holdings to the weights of foreign assets investors would need to hold if the International Capital Asset Pricing Model was their point of reference. These data are available at annual frequency from 2001 onwards. We detail the construction of this asset market home-bias measure in the Internet Appendix.

Table A.I in the Internet Appendix reports results for panel regression (with time fixed effects) where we regress our value signal on one or both of the two home bias measures, and

[14]Some authors argue that in theory consumption home bias and financial home bias are positively related (e.g., Stockman and Dellas, 1989).

with and without including our other fundamentals as controls.

As can be seen from specifications (i) and (ii), a larger degree of home bias in trade is actually associated with a higher value signal (i.e., a weaker RER). Yet, this this link is not statistically significant. For the financial home bias measure, we find insignificant slope coefficients, too (specifications (iii) and (iv)). Finally, specification (v) shows that both measures are insignificant when included jointly in the regression and when controlling for the other fundamentals. Hence, conventional measures of home bias do not seem to drive the cross-sectional variation of currency valuations in our sample.

### 5.5 Value portfolios based on absolute PPP

Our benchmark value signal is based on 5-year changes in RER levels computed from spot exchange rates and CPI inflation and is normalized to unity in 1970Q1. For robustness, we also compute portfolio returns based on a measure of RER that is immune to the base year and computed from actual disaggregated product prices. These data are taken from the OECD but are only updated every three years. Another downside is that the OECD data are available at annual frequency only and cover a smaller set of currencies. Hence, we only use this set of absolute RERs for this robustness check. Table A.II in the Internet Appendix shows results for portfolios based on 5-year changes in absolute RERs and we find that the results are overall similar to those in Table 4.

### 5.6 Cross-validation: Influential currencies

To rule out the possibility that our main result is driven by one particular currency, we provide results from a cross-validation exercise in Table A.III in the Internet Appendix. More specifically, we drop one currency at a time, control for macro fundamentals, and compute returns to the modified value strategies ($\varepsilon^{Q}$) as in Table 5. The rows in Table A.III indicate which currency was excluded from the sample. Overall, we find that our results are robust and are not driven by one particular outlier currency.

### 5.7 Implementation lags

We repeat the analysis underlying Table 5 and build currency portfolios based on value signals purged from expected fundamentals. However, we allow for an additional two quarters between observing the signals and forming the portfolio, i.e. we add an implementation lag of two quarters to account for the fact that macro fundamentals are reported with a lag.[15] We find that lagging the value signal clearly reduces mean returns and Sharpe Ratios for all portfolios. However, we still find the same general pattern in portfolio returns as in our benchmark analyses above: Portfolios based on raw value signals (RER) have clearly lower average returns and Sharpe Ratios than portfolios based on controlling for expected fundamentals ($\varepsilon^Q$). This result is also related to our finding in Figure 1 above, which shows that controlling for fundamentals leads to more persistent predictability than using the raw value signal (5-year RER changes).

## 6 Conclusion

The valuation of currencies is of key importance to policy makers and investors alike, but empirical evidence on the properties and determinants of "currency value" is still scattered and largely incomplete. This is unfortunate as currency value measures based on the real exchange rate are commonly used for practical purposes, e.g. when gauging currency misalignments or for the design of currency investment and hedging strategies.

We contribute to the literature by investigating the predictive content of both real exchange rates and real exchange rates adjusted for macroeconomic fundamentals for currency

[15]Ideally, one would want to use vintage data for this exercise. However, these data do not exist for our sample and set of fundamentals. Using an implementation lag of two quarters can thus be seen as a rough approximation only.

excess returns. Our ultimate goal is to provide a better understanding of the link between currency valuation and risk premia in a large cross-section of currencies. This is important in light of recent work by Hassan and Mano (2015), suggesting that currency premia are largely static and ultimately driven by persistent currency characteristics.

We find that real exchange rates forecast the cross-section of currency excess returns but that more powerful value signals can be obtained when adjusting real exchange rates for standard fundamentals from the international finance literature. The fundamentals we use in our empirical analysis are productivity (Harrod-Balassa-Samuelson effects), export quality, net foreign assets, and output gaps.

Overall, these results are encouraging given the well-documented empirical difficulties of models of exchange rate equilibrium, and should spur further research in several directions. Most importantly, while this paper has a strong asset pricing focus, our results have implications for international macro models of exchange rate determination and for theoretical work. An immediate avenue for further research is the development of a clear theoretical framework that can fully specify the economic mechanisms that imply how a weak RER is contemporaneously associated with a high currency risk premium. This could conceivably be achieved, for example, by incorporating deviations from PPP in a model of rare disaster with mean reversion under complete markets (as in Farhi and Gabaix, 2015) or by extending the incomplete markets model with financial frictions of Gabaix and Maggiori (2015) to allow for quality of exports and productivity differentials. This remains an important avenue for further research.

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**Table 1.** Descriptive statistics

This table reports descriptive statistics for excess returns ($RX$), exchange rate changes ($\Delta S$), the log RER ($q$), (log) RER changes ($\Delta q$), and inflation differentials ($\Delta\pi$). All quantities and growth rates are differentials (against the USD/U.S.). Except for the (log) real exchange rate $q$, all other variables are in percent and annualized. The sample period is 1976Q1 – 2014Q1 and the frequency is quarterly.

| | $RX$ | | $\Delta S$ | | $q$ | | $\Delta q$ | | $\Delta\pi$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ |
| Australia | 2.68 | 7.89 | -0.20 | 7.69 | -0.14 | 0.06 | -10.04 | 32.47 | 1.02 | 1.52 |
| Canada | 1.41 | 4.55 | -0.02 | 4.50 | 0.07 | 0.04 | 1.25 | 21.91 | -0.08 | 0.90 |
| France | 1.87 | 8.49 | -0.28 | 8.38 | -0.24 | 0.06 | -7.06 | 37.05 | 0.60 | 1.05 |
| Germany | 1.55 | 8.32 | 2.28 | 8.26 | -0.26 | 0.06 | -2.34 | 36.64 | -1.50 | 1.23 |
| Hungary | 6.45 | 9.56 | -3.18 | 8.85 | -0.20 | 0.09 | -21.48 | 32.88 | 5.67 | 3.85 |
| India | 2.39 | 4.76 | -4.68 | 5.05 | 0.48 | 0.10 | 28.98 | 28.15 | 3.74 | 3.58 |
| Indonesia | 4.38 | 12.41 | -6.45 | 13.76 | 0.51 | 0.16 | 35.65 | 57.33 | 5.10 | 5.41 |
| Italy | 2.64 | 8.36 | -3.11 | 8.34 | -0.14 | 0.05 | -3.98 | 33.70 | 3.92 | 1.72 |
| Japan | 1.23 | 9.22 | 3.64 | 9.09 | -0.72 | 0.07 | -24.26 | 34.80 | -2.31 | 1.22 |
| Korea | 4.03 | 8.26 | -1.28 | 8.07 | 0.06 | 0.05 | 0.76 | 30.69 | 2.01 | 1.87 |
| Mexico | 4.38 | 13.30 | -15.48 | 13.40 | 0.05 | 0.07 | 4.42 | 41.38 | 17.66 | 8.53 |
| New Z. | 7.69 | 8.72 | 0.16 | 7.88 | -0.27 | 0.07 | -17.42 | 37.23 | 1.85 | 1.93 |
| Norway | 2.00 | 7.74 | 0.38 | 7.52 | -0.33 | 0.05 | -9.49 | 30.30 | 0.35 | 1.58 |
| Singapore | -0.02 | 3.78 | 1.91 | 3.69 | -0.19 | 0.04 | -5.43 | 24.10 | -1.50 | 1.52 |
| S. Africa | 0.32 | 10.38 | -5.43 | 10.09 | 0.24 | 0.08 | 19.31 | 38.32 | 5.41 | 1.85 |
| Spain | 2.72 | 8.53 | -3.05 | 8.30 | -0.49 | 0.07 | -22.48 | 45.46 | 4.06 | 1.95 |
| Sweden | 1.43 | 7.98 | -0.36 | 7.96 | -0.04 | 0.06 | 10.18 | 37.26 | 0.39 | 1.57 |
| Switzerland | 1.13 | 9.04 | 3.67 | 9.21 | -0.66 | 0.06 | -26.65 | 36.51 | -1.93 | 1.28 |
| Taiwan | 0.38 | 3.86 | 0.73 | 3.89 | -0.29 | 0.05 | -2.43 | 23.97 | -0.88 | 2.35 |
| Thailand | 0.97 | 6.82 | -0.71 | 6.69 | 0.10 | 0.07 | 9.16 | 28.78 | 0.30 | 1.90 |
| Turkey | 14.93 | 12.56 | -28.18 | 12.18 | 0.01 | 0.09 | -5.33 | 43.88 | 30.72 | 9.03 |
| U.K. | 2.22 | 7.49 | 0.04 | 7.35 | -0.32 | 0.05 | -12.82 | 28.82 | 1.26 | 1.44 |

**Table 2.** Predictive power of macroeconomic fundamentals for real interest rate differentials

This table reports $p$-values for tests of a link between macro fundamentals and subsequent real interest rate differentials (RIDs). We adopt a Granger causality type setting and regress RIDs on lagged RIDs, real per-capita GDP (HBS), export quality (Qual), net foreign assets scaled by GDP (NFA), and output gaps (OG). $h$ denotes the forecast horizon (years). The results are based on panel regressions which include time fixed effects (year fixed effects). $t$-statistics are based on two-way clustered standard errors (clustered by currency and quarter). The sample period is 1976 – 2013 and the frequency is annual.

| $h$ | RID | HBS | Qual | NFA | OG |
|---|---|---|---|---|---|
| 1 | 0.020 | 0.029 | 0.017 | 0.028 | 0.098 |
| 2 | 0.446 | 0.596 | 0.017 | 0.105 | 0.026 |
| 3 | 0.179 | 0.147 | 0.023 | 0.164 | 0.048 |
| 4 | 0.154 | 0.043 | 0.065 | 0.197 | 0.085 |
| 5 | 0.159 | 0.128 | 0.142 | 0.114 | 0.087 |

**Table 3.** Regressions of excess returns on 5-year RER changes and controls

This table reports results for panel regressions of excess returns on lagged 5-year RER changes and further control variables. These control variables include: real interest rate differentials (RID), real per-capita GDP (HBS), export quality (Qual), net foreign assets scaled by GDP (NFA), and output gaps (OG). We report the slope estimate ($b$) for 5-year RER changes, the associated $t$-statistic (in brackets), the (adjusted) $R^2$ (in %), and the incremental $R^2$ (denoted $\Delta R^2$) when adding 5-year RER changes to the regression. The upper panel shows results for specifications where the real interest rate is included in all specifications except (i). The lower panel excludes RIDs everywhere. The final rows of each panel indicate which control variables are included in the regression. All panel regressions include time fixed effects (quarterly basis). $t$-statistics are based on two-way clustered standard errors (clustered by currency and quarter). The sample period is 1976Q1 – 2014Q1 and the frequency is quarterly.

| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) |
|---|---|---|---|---|---|---|---|
| | | | Panel A: Controlling for RIDs | | | | |
| $b$ | 0.027 | 0.029 | 0.032 | 0.031 | 0.031 | 0.034 | 0.039 |
| $t$ | [3.24] | [3.37] | [3.66] | [3.49] | [3.52] | [3.72] | [4.46] |
| $R^2$ | 0.81 | 2.75 | 3.96 | 2.82 | 2.89 | 4.73 | 5.38 |
| $\Delta R^2$ | | 0.83 | 0.99 | 0.88 | 0.89 | 1.10 | 1.34 |
| Controls | | RID | RID | RID | RID | RID | All |
| | | | HBS | Qual | NFA | OG | |
| | | | Panel B: Excluding RIDs | | | | |
| $b$ | | | 0.031 | 0.028 | 0.029 | 0.033 | 0.043 |
| $t$ | | | [3.69] | [3.38] | [3.50] | [3.67] | [4.37] |
| $R^2$ | | | 3.01 | 0.81 | 1.04 | 3.86 | 4.72 |
| $\Delta R^2$ | | | 0.93 | 0.77 | 0.80 | 1.06 | 1.32 |
| Controls | | | HBS | Qual | NFA | OG | All |

**Table 4.** Returns to currency value strategies

This table reports descriptive statistics for currency portfolios based on 5-year real exchange rate changes. We report results for cross-sectional portfolio sorts where we sort currencies into 4 bins based on the cross section of signals (portfolios $P_1, ..., P_4$ and a high minus low portfolio, HML, long $P_4$ and short $P_1$), as well as a rank portfolio ($PF^R$), and a simple portfolio based on linear portfolio weights ($PF^L$; weights are linear in the cross-sectional deviation of signals from the cross-sectional mean). Real exchange rates are defined such that a higher real exchange rate indicates a weaker foreign currency. Hence, the portfolios go long currencies with a relatively low valuation and go short currencies with a relatively high valuation. Excess returns are defined such that positive numbers mean a positive return on holding the foreign currency. Mean returns, return volatilities ($\sigma$), and Sharpe Ratios (SR) are annualized. $t$-statistics in brackets are based on Newey and West (1987) standard errors. The sample period is 1976Q1 – 2014Q1 and the frequency is quarterly.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | HML | $PF^R$ | $PF^L$ |
|---|---|---|---|---|---|---|---|
| mean | 1.11 | 1.00 | 2.92 | 5.00 | 3.89 | 3.65 | 2.32 |
| $t$ | [0.57] | [0.65] | [2.00] | [3.75] | [2.15] | [2.61] | [2.73] |
| $\sigma$ | 9.44 | 8.22 | 7.62 | 7.78 | 8.93 | 7.27 | 4.57 |
| SR | 0.12 | 0.12 | 0.38 | 0.64 | 0.44 | 0.50 | 0.51 |

**Table 5.** Currency value strategies accounting for fundamentals

This table reports excess returns for portfolios formed on 5-year RER changes and a decomposition into the part of RER related to macro fundamentals ($\widehat{Q}$) and a part unrelated to these fundamentals ($\varepsilon^Q$). We regress 5-year RER changes on real per-capita GDP, export quality, net foreign assets scaled by GDP, and output gaps in the cross-section each quarter to obtain the fitted RER (Fund) and the residual ($\varepsilon^Q$). We then build linear-weight and rank portfolios based on these two components. We use four different measures of fundamentals in these cross-sectional regressions: Panel (a) simply uses the raw fundamentals whereas the remaining panels use proxies for expected fundamentals. Panel (b) uses an exponentially-weighted moving average (EWMA), Panel (c) employs expected fundamentals from VARs (estimated recursively and separately for each country), and Panel (d) uses a (recursive) panel VAR to compute expected fundamentals. We report annualized mean excess returns, $t$-statistics based on Newey-West standard errors in squared brackets, the annualized excess return volatility ($\sigma$), and annualized Sharpe Ratios (SR). The sample period is 1976Q1 – 2014Q1 (at most) and the frequency is quarterly.

| | Linear portfolios | | | Rank portfolios | | |
|---|---|---|---|---|---|---|
| | RER | $\widehat{Q}$ | $\varepsilon^Q$ | RER | $\widehat{Q}$ | $\varepsilon^Q$ |
| Panel A. Raw fundamentals | | | | | | |
| mean | 2.67 | 0.54 | 2.13 | 4.16 | 2.05 | 4.12 |
| $t$ | [2.93] | [0.95] | [4.12] | [2.84] | [1.38] | [4.17] |
| $\sigma$ | 4.93 | 3.61 | 2.68 | 7.85 | 8.61 | 5.22 |
| SR | 0.54 | 0.15 | 0.79 | 0.53 | 0.24 | 0.79 |
| Panel B. Expected fundamentals (EWMA) | | | | | | |
| mean | 3.00 | 0.26 | 2.74 | 4.67 | 1.23 | 4.76 |
| $t$ | [2.98] | [0.40] | [4.30] | [2.91] | [0.82] | [4.12] |
| $\sigma$ | 5.10 | 3.56 | 3.04 | 8.06 | 8.40 | 5.85 |
| SR | 0.59 | 0.07 | 0.90 | 0.58 | 0.15 | 0.81 |
| Panel C. Expected fundamentals (VAR) | | | | | | |
| mean | 3.04 | 0.82 | 2.22 | 4.76 | 2.88 | 4.86 |
| $t$ | [3.09] | [1.33] | [4.15] | [3.03] | [1.78] | [5.02] |
| $\sigma$ | 5.08 | 3.87 | 2.62 | 8.05 | 9.02 | 5.35 |
| SR | 0.60 | 0.21 | 0.85 | 0.59 | 0.32 | 0.91 |
| Panel D. Expected fundamentals (Panel VAR) | | | | | | |
| mean | 3.04 | 0.61 | 2.43 | 4.76 | 2.37 | 4.67 |
| $t$ | [3.09] | [0.98] | [4.52] | [3.03] | [1.44] | [4.61] |
| $\sigma$ | 5.08 | 3.77 | 2.68 | 8.05 | 9.00 | 5.19 |
| SR | 0.60 | 0.16 | 0.91 | 0.59 | 0.26 | 0.90 |

**Table 6.** Currency value: Exposure regressions

This table reports exposure regression results in Panel A and weights in global tangency portfolios in Panel B. The dependent variable in Panel A. is the excess return of a value portfolio based on 5-year RER changes controlling for macro fundamentals (see Panel D. in Table 5, denotes Res here). As factors in the regressions, we include excess returns to carry trades, momentum, standard value (5-year RER changes, ΔRER), and the global imbalances factor ($IMB$) of Della Corte et al in various different specifications. $R^2$ denotes the (adjusted) regression $R^2$ whereas $IR$ denotes the information ratio (alpha divided by residual standard deviation). Alphas and information ratios are annualized and in percent. The sample period is 1980Q3 – 2014Q1 for all specifications not involving $IMB$ and 1983Q4-2013Q4 for specifications involving $IMB$ due to data availability. Numbers in squared brackets are $t$-statistics based on Newey and West (1987) standard errors.

| | (i) | (ii) | (iii) | (iv) | (v) | (vi)] |
|---|---|---|---|---|---|---|
| | | | Panel A. Exposure regressions | | | |
| $\alpha$ | 4.67 | 4.62 | 2.31 | 4.09 | 3.60 | 2.06 |
| | [4.61] | [4.49] | [3.24] | [4.31] | [3.79] | [2.64] |
| Carry | | 0.06 | 0.07 | | 0.13 | 0.12 |
| | | [0.87] | [1.06] | | [1.82] | [1.69] |
| Mom | | -0.12 | 0.03 | | -0.14 | 0.03 |
| | | [-1.69] | [0.57] | | [-2.14] | [0.48] |
| ΔRER | | | 0.45 | | | 0.44 |
| | | | [8.40] | | | [7.52] |
| $IMB$ | | | | 0.07 | 0.07 | 0.01 |
| | | | | [0.85] | [0.87] | [0.16] |
| $R^2$ | | 2.97 | 39.59 | -0.05 | 7.07 | 40.60 |
| $IR$ | 0.90 | 0.91 | 0.58 | 0.80 | 0.73 | 0.53 |
| | | | Panel B. Tangency portfolio weights | | | |
| Carry | 0.32 | 0.22 | 0.22 | | 0.22 | 0.22 |
| | [3.78] | [2.77] | [2.97] | | [2.96] | [3.17] |
| Mom | 0.30 | 0.19 | 0.21 | | 0.15 | 0.16 |
| | [3.07] | [2.41] | [2.37] | | [2.14] | [1.91] |
| ΔRER | 0.38 | | 0.13 | | | 0.04 |
| | [3.19] | | [0.88] | | | [0.34] |
| $IMB$ | | | | 0.35 | 0.24 | 0.23 |
| | | | | [2.93] | [3.42] | [3.06] |
| Res | | 0.59 | 0.45 | 0.65 | 0.39 | 0.35 |
| | | [5.20] | [2.89] | [4.37] | [3.20] | [2.39] |

**Table 7.** Macroeconomic fundamentals as drivers of real exchange rates

This table reports results for panel regressions of 5-year RER changes on macro fundamentals. These fundamentals are: real per-capita GDP (HBS), export quality (Qual), net foreign assets scaled by GDP (NFA), and output gaps (OG). All panel regressions include time fixed effects (quarterly basis). $t$-statistics are based on two-way clustered standard errors (clustered by currency and quarter). The sample period is 1976Q1 – 2014Q1 and the frequency is quarterly. We report the simple $R^2$ for specifications (i) – (iv) and the adjusted $R^2$ for specification (v).

| | (i) | (ii) | (iii) | (iv) | (v) |
|---|---|---|---|---|---|
| HBS | -0.11 | | | | -0.22 |
| | [-2.18] | | | | [-8.90] |
| Qual | | -0.32 | | | -0.42 |
| | | [-5.00] | | | [-4.80] |
| NFA | | | -0.02 | | 0.02 |
| | | | [-0.72] | | [0.62] |
| OG | | | | -0.08 | -1.04 |
| | | | | [-1.79] | [-7.65] |
| $R^2$ | 0.12 | 0.33 | 0.14 | 0.16 | 0.28 |

**Table 8.** Decomposing currency value signals

This table reports results for portfolios based on the RER level ($q_t$), the lagged RER level 5 years ago ($q_{t-5y}$), the 5-year change in the RER ($\Delta q_{t-5y;t}$), the negative of 5-year inflation differentials ($-\Delta^* \pi_{t-5y;t}$), and the negative of 5-year nominal spot exchange rate changes ($-\Delta s_{t-5y;t}$). Panel A shows results for linear portfolios where we can compute an exact decomposition of returns whereas Panel B shows results for rank portfolios. Portfolio weights are updated quarterly.

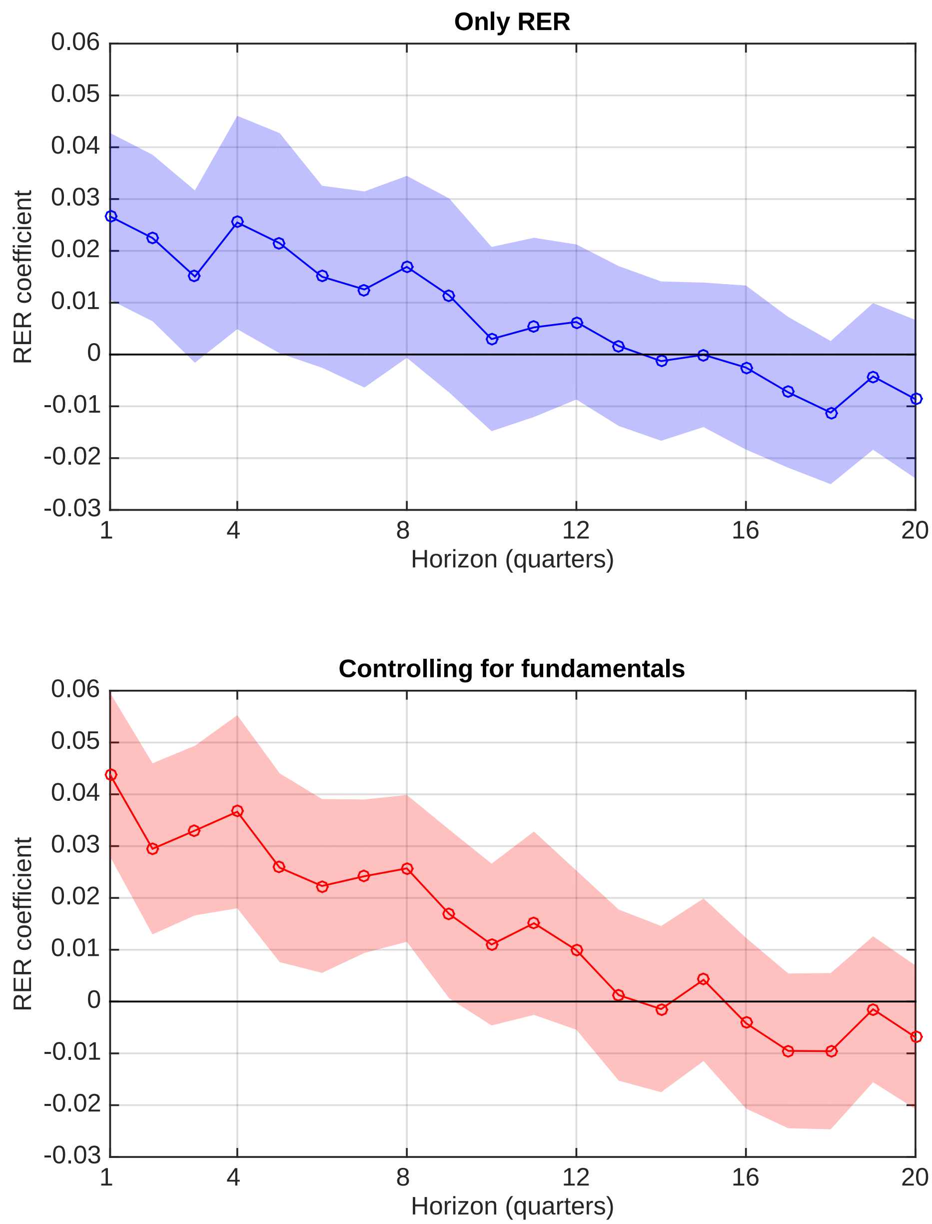
| | Panel A. Linear portfolios | | | | |
|---|---|---|---|---|---|
| | $q_t$ | $q_{t-5y}$ | $\Delta q_{t-5y;t}$ | $-\Delta^* \pi_{t-5y;t}$ | $-\Delta s_{t-5y;t}$ |
| mean | 3.95 | 1.62 | 2.32 | -11.74 | 14.07 |
| $t$ | [2.67] | [1.21] | [2.73] | [-3.10] | [3.48] |
| $\sigma$ | 9.59 | 8.83 | 4.57 | 16.59 | 17.41 |
| SR | 0.41 | 0.18 | 0.51 | -0.71 | 0.81 |
| | Panel B. Rank portfolios | | | | |
| | $q_t$ | $q_{t-5y}$ | $\Delta q_{t-5y}$ | $-\Delta^* \pi_{t-5y;t}$ | $-\Delta s_{t-5y;t}$ |
| mean | 2.43 | 1.43 | 3.65 | -4.45 | 5.87 |
| $t$ | [2.02] | [1.04] | [2.61] | [-3.37] | [4.00] |
| $\sigma$ | 7.81 | 8.26 | 7.27 | 7.50 | 7.81 |
| SR | 0.31 | 0.17 | 0.50 | -0.59 | 0.75 |

**Table 9.** Value vs. Carry: Sequential portfolio sorts

This table reports results for sequential portfolios where we split the sample of currencies into two buckets depending on the median value of one characteristic in quarter $t$ and then form rank portfolios separately within these two buckets according to a second characteristic and compute returns to these portfolios in quarter $t+1$. The results on the left (right) side of the table are based on first splitting the sample according to value (carry) and forming separate portfolios based on carry (value). Portfolios are updated quarterly. The sample period is 1976Q1 – 2014Q1 and the frequency is quarterly.

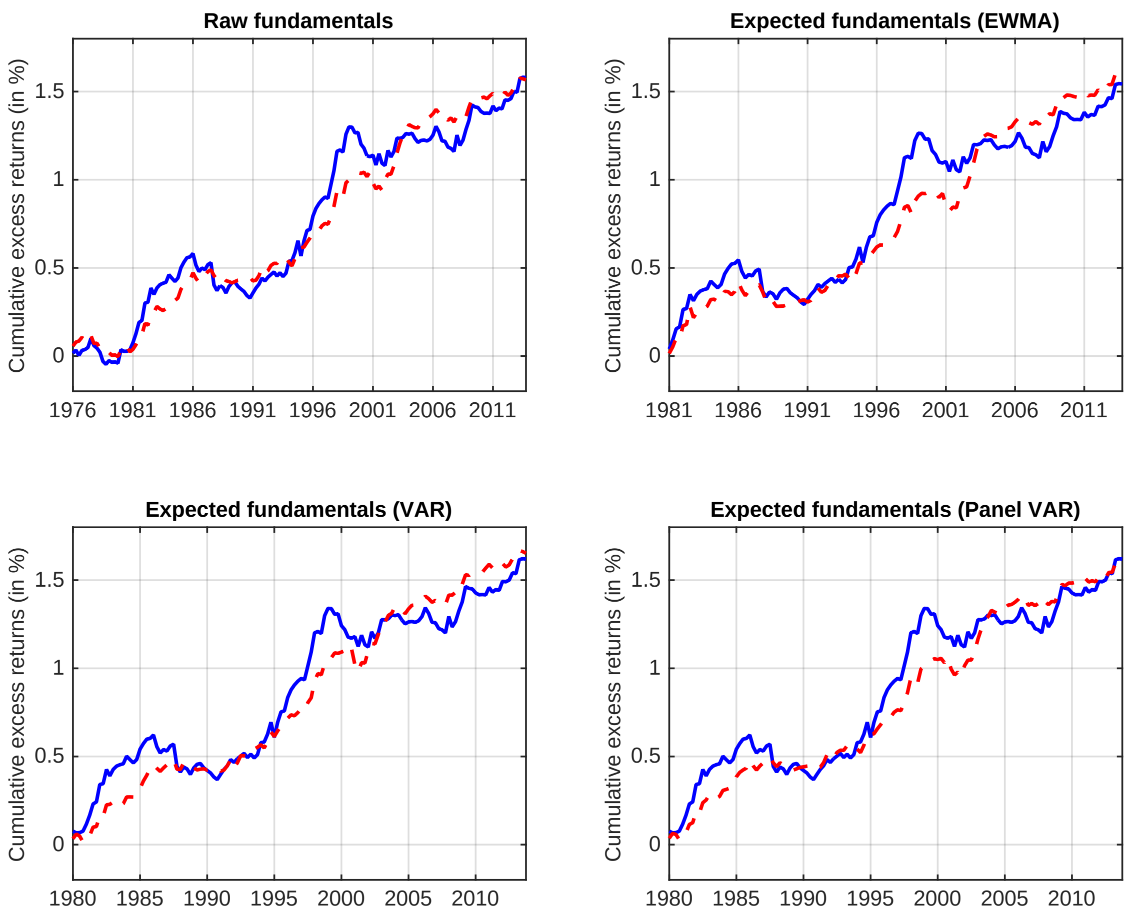
| | Value portfolios | | Carry portfolios | |
|---|---|---|---|---|
| | Low carry | High carry | Low value | High value |
| mean | 4.50 | 5.01 | 5.53 | 6.13 |
| $t$ | [3.61] | [2.18] | [2.20] | [3.56] |
| $\sigma$ | 8.41 | 10.96 | 12.16 | 10.65 |
| SR | 0.53 | 0.46 | 0.45 | 0.57 |

**Figure 1.** Impulse-response functions: Excess returns



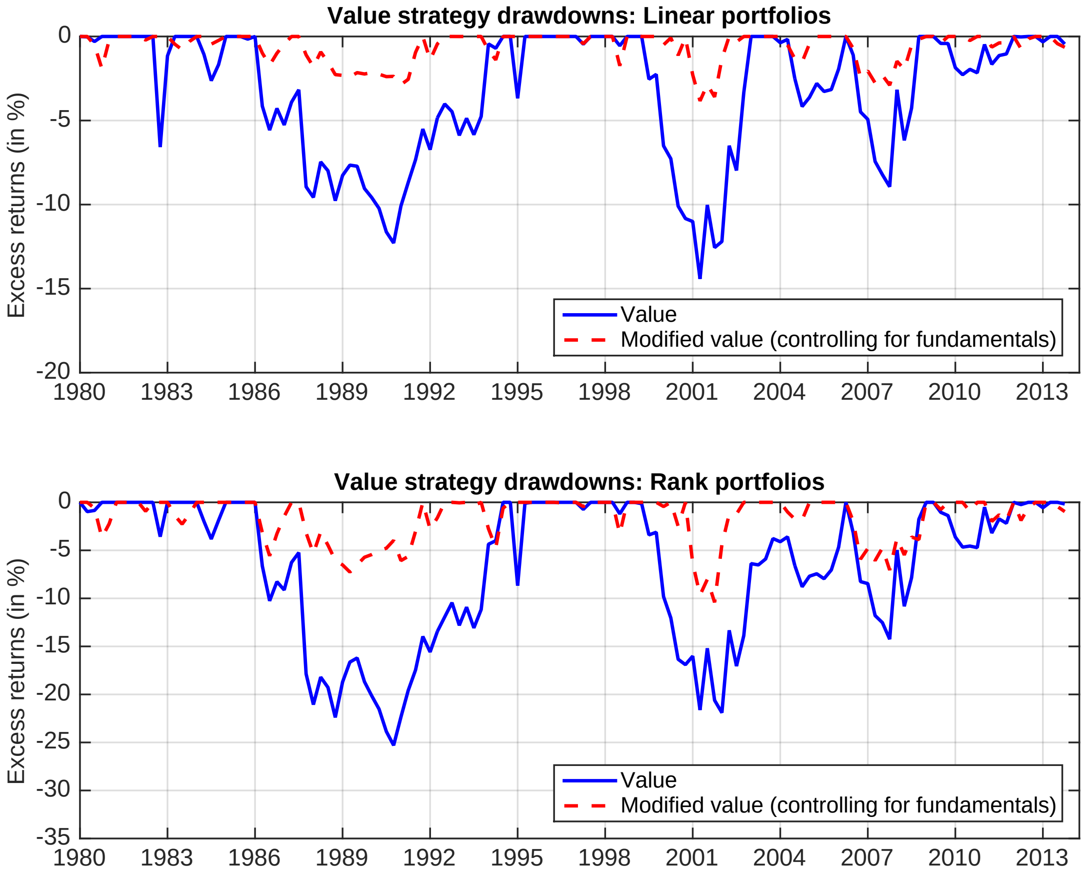

This figure plots the impulse response of excess returns to movements in 5-year RER changes. The plots are based on local projections as in Jorda (2005) and we employ panel regressions with time fixed effects to estimate the projection coefficients. Shaded areas indicate 95% confidence intervals which are based on two-way clustered standard errors (clustered by currency and quarter). The upper plot shows the response of excess returns for a specification where only include lagged 5-year RERs in the regressions (as well as lagged excess returns) whereas the lower plot shows the response of excess returns when additionally controlling for lagged macro fundamentals (real interest rate differentials, HBS, export quality, net foreign assets scaled by GDP, output gaps (OG).

**Figure 2.** Cumulative excess returns to currency value strategies




This figure plots cumulative portfolio excess returns for value strategies. The blue solid lines refer to standard value strategies (based on 5-year RER changes) whereas the red dashed lines refer to modified value strategies ($\varepsilon^Q$) which control for (expected) macro fundamentals. The four cases shown refer to the different ways of controlling for (expected) fundamentals documented in Table 5.

**Figure 3.** Drawdowns of currency value strategies




This figure plots the drawdown dynamics of portfolios based on 5-year RER changes (solid line) and based on a value measure that controls for macro fundamentals (see Panel (d) in Table 5). The upper plot shows drawdowns for linear portfolios and the lower plot shows drawdowns for rank portfolios.

*Supplementary Internet Appendix to accompany*

# Currency Value

**Table A.I.** Home bias and currency value

This table reports reports results for panel regressions of value signals (5-year changes in RER) on two measures of home bias. The first measure is a proxy for home bias in trade (HB trade) and refers to the share of imports relative to total GDP of a country. The second measure is a proxy for financial home bias (HB fin) and is based on portfolio equity holdings (Holdings of domestic equities by residents of the respective country relative to an international CAPM benchmark). We run regressions of RER on these measures separately and jointly as well as with and without controlling for the other fundamentals (HBS, quality, NFA/GDP, output gaps). The sample period is 1976Q1 – 2014Q1 for import shares and the sample for the home bias measure based on portfolio holdings starts in 2001.

| $h$ | (i) | (ii) | (iii) | (iv) | (v) |
|---|---|---|---|---|---|
| HB trade | 1.970 | 1.348 | | | 1.198 |
| | [1.53] | [1.16] | | | [0.88] |
| HB fin | | | -0.024 | 0.017 | 0.015 |
| | | | [-0.59] | [0.41] | [0.33] |
| Controls | NO | YES | NO | YES | YES |
| $R^2$ | 0.02 | 0.29 | 0.00 | 0.41 | 0.40 |

**Table A.II.** Currency value portfolios based on absolute PPP rates

This table reports returns to value strategies based on 5-year changes in real exchange rates where we construct RERs from absolute PPP rates (available from the OECD). For these PPP series, we do not need to normalize the real exchange rate in some base year. We only update portfolio weights annually as OECD PPP rates are only available on an annual frequency. $t$-statistics in brackets are based on Newey and West (1987) standard errors. The sample period is 1976 – 2014.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | HML | $PF^R$ | $PF^L$ |
|---|---|---|---|---|---|---|---|
| | | | | Excess returns | | | |
| mean | -1.40 | 2.88 | 4.97 | 2.11 | 3.52 | 2.95 | 3.23 |
| $t$ | [-0.74] | [1.86] | [2.98] | [1.38] | [4.15] | [4.12] | [4.20] |
| std | 10.25 | 8.75 | 7.95 | 7.87 | 4.86 | 4.55 | 4.96 |
| SR | -0.14 | 0.33 | 0.63 | 0.27 | 0.73 | 0.65 | 0.65 |

**Table A.III.** Impact of influential currencies: Cross-validation exercise

This table shows results for a cross-validation exercise of portfolio returns. More specifically, we eliminate one country at a time from the investment universe and then compute returns to rank portfolios based on 5-year RER changes and controlling for fundamentals according to the four cases in Table 5. Table rows indicate which country is excluded. We report (annualized) mean excess returns and Sharpe Ratios (SR). $t$-statistics in brackets are based on Newey/West standard errors. The sample period is 1976Q1 – 2014Q1 (at most) and the frequency is quarterly.

| | Raw fundamentals | | | EWMA | | | VAR | | | Panel VAR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | $t$ | $SR$ | mean | $t$ | $SR$ | mean | $t$ | $SR$ | mean | $t$ | $SR$ |
| Australia | 3.83 | [3.77] | 0.71 | 4.54 | [3.78] | 0.76 | 4.61 | [4.51] | 0.84 | 4.33 | [4.13] | 0.81 |
| Canada | 4.22 | [4.15] | 0.78 | 4.76 | [3.93] | 0.78 | 4.81 | [4.66] | 0.86 | 4.67 | [4.38] | 0.86 |
| France | 4.02 | [3.98] | 0.76 | 4.76 | [4.03] | 0.78 | 4.90 | [5.04] | 0.92 | 4.65 | [4.57] | 0.88 |
| Germany | 4.08 | [3.90] | 0.74 | 4.75 | [3.86] | 0.76 | 4.81 | [4.87] | 0.86 | 4.76 | [4.50] | 0.87 |
| Hungary | 4.15 | [3.96] | 0.76 | 4.70 | [3.79] | 0.76 | 4.90 | [4.64] | 0.86 | 4.71 | [4.34] | 0.86 |
| India | 4.43 | [4.24] | 0.81 | 5.02 | [4.21] | 0.82 | 5.24 | [5.17] | 0.95 | 5.02 | [4.67] | 0.92 |
| Indonesia | 4.14 | [4.10] | 0.78 | 4.79 | [4.03] | 0.80 | 4.84 | [5.02] | 0.90 | 4.69 | [4.51] | 0.88 |
| Italy | 4.48 | [4.37] | 0.83 | 5.13 | [4.35] | 0.86 | 5.19 | [5.12] | 0.96 | 5.05 | [4.78] | 0.94 |
| Japan | 3.86 | [3.71] | 0.71 | 4.45 | [3.75] | 0.73 | 4.74 | [4.53] | 0.85 | 4.33 | [4.07] | 0.80 |
| S. Korea | 3.40 | [3.56] | 0.67 | 4.24 | [3.60] | 0.71 | 4.08 | [4.21] | 0.75 | 3.88 | [3.93] | 0.76 |
| Mexico | 3.99 | [4.40] | 0.74 | 4.56 | [4.46] | 0.81 | 4.43 | [5.66] | 0.83 | 4.54 | [4.97] | 0.84 |
| New Z. | 4.22 | [4.27] | 0.81 | 4.93 | [4.27] | 0.85 | 4.98 | [5.21] | 0.93 | 4.77 | [4.73] | 0.93 |
| Norway | 4.31 | [4.11] | 0.80 | 4.88 | [4.00] | 0.80 | 5.05 | [4.87] | 0.90 | 4.90 | [4.62] | 0.92 |
| Singapore | 4.12 | [4.17] | 0.79 | 4.76 | [4.12] | 0.81 | 4.86 | [5.02] | 0.91 | 4.67 | [4.61] | 0.90 |
| S. Africa | 3.70 | [3.91] | 0.69 | 4.47 | [4.04] | 0.74 | 4.26 | [4.71] | 0.78 | 4.21 | [4.40] | 0.79 |
| Spain | 4.19 | [4.21] | 0.79 | 4.95 | [4.19] | 0.82 | 5.00 | [5.10] | 0.91 | 4.75 | [4.63] | 0.89 |
| Sweden | 4.32 | [4.14] | 0.78 | 4.99 | [4.04] | 0.81 | 5.09 | [4.93] | 0.90 | 4.93 | [4.61] | 0.90 |
| Switzerland | 4.20 | [4.02] | 0.76 | 4.82 | [3.95] | 0.79 | 5.03 | [4.77] | 0.91 | 4.76 | [4.40] | 0.86 |
| Taiwan | 4.12 | [4.17] | 0.79 | 4.76 | [4.12] | 0.81 | 4.86 | [5.02] | 0.91 | 4.67 | [4.61] | 0.90 |
| Thailand | 4.22 | [3.90] | 0.76 | 4.77 | [3.85] | 0.77 | 4.95 | [4.78] | 0.90 | 4.73 | [4.14] | 0.85 |
| Turkey | 4.05 | [3.98] | 0.77 | 4.57 | [4.19] | 0.80 | 4.89 | [4.78] | 0.89 | 4.59 | [4.38] | 0.88 |
| U.K. | 4.37 | [4.21] | 0.80 | 4.86 | [4.00] | 0.79 | 5.18 | [4.88] | 0.90 | 4.87 | [4.47] | 0.89 |

**Table A.IV.** Portfolio excess returns: Two quarters implementation lag

This table is the same as Table 5 in the main text but here we allow for an additional two quarters between observing the signal and forming rank portfolios.

| | Linear portfolios | | | Rank portfolios | | |
|---|---|---|---|---|---|---|
| | RER | $\widehat{Q}$ | $\varepsilon^Q$ | RER | $\widehat{Q}$ | $\varepsilon^Q$ |
| | | | Panel A. Untransformed fundamentals | | | |
| mean | 1.51 | 0.35 | 1.15 | 2.52 | 1.42 | 2.06 |
| $t$ | [2.00] | [0.62] | [2.54] | [1.96] | [0.98] | [2.19] |
| $\sigma$ | 4.85 | 3.89 | 2.37 | 8.46 | 9.82 | 5.25 |
| SR | 0.31 | 0.09 | 0.49 | 0.30 | 0.14 | 0.39 |
| | | | Panel B. Expected fundamentals (EWMA) | | | |
| mean | 1.70 | -0.03 | 1.73 | 2.93 | 1.24 | 3.02 |
| $t$ | [2.05] | [-0.05] | [3.24] | [2.10] | [0.77] | [2.69] |
| $\sigma$ | 5.02 | 3.93 | 2.89 | 8.71 | 9.44 | 5.70 |
| SR | 0.34 | -0.01 | 0.60 | 0.34 | 0.13 | 0.53 |
| | | | Panel C. Expected fundamentals (VAR) | | | |
| mean | 1.74 | 0.33 | 1.41 | 3.03 | 1.29 | 3.11 |
| $t$ | [2.12] | [0.52] | [3.02] | [2.18] | [0.87] | [3.42] |
| $\sigma$ | 4.97 | 4.03 | 2.46 | 8.63 | 9.69 | 5.40 |
| SR | 0.35 | 0.08 | 0.57 | 0.35 | 0.13 | 0.58 |
| | | | Panel D. Expected fundamentals (Panel VAR) | | | |
| mean | 1.74 | 0.30 | 1.44 | 3.03 | 1.37 | 2.49 |
| $t$ | [2.12] | [0.47] | [3.12] | [2.18] | [0.85] | [2.59] |
| $\sigma$ | 4.97 | 4.02 | 2.37 | 8.63 | 10.14 | 5.23 |
| SR | 0.35 | 0.07 | 0.61 | 0.35 | 0.14 | 0.48 |