Currency Value*

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This version: June 8, 2016

*Forthcoming in the *Review of Financial Studies*. We are grateful to Stefan Nagel (the Editor), an anonymous Referee, Klaus Adam, Christiane Baumeister, Alessandro Beber, Yin-Wong Cheung, Menzie Chinn, Charles Engel, Marcel Fratzscher, Gabriele Galati, Harald Hau, Burton Hollifield, Tim Kroencke, Nelson Mark, Michael Melvin, Lasse Pedersen, Angelo Ranaldo, Jesper Rangvid, Dagfinn Rime, Barbara Rossi, Laurens Swinkels, Adrien Verdelhan, Michael Weber and participants at the ASSA meetings (2016), European Finance Association meetings (2015), ECB-BdI conference on the financial determinants of exchange rates (2015), INQUIRE UK (2015), ECB-BoC workshop "Exchange rates: A global perspective" (2013), Bank for International Settlements, Norges Bank Investment Management, and seminar participants at various universities for helpful comments and suggestions. An earlier draft of this paper circulated under the title "Currency Risk Premia and Macro Fundamentals". The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank for International Settlements (BIS).

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Abstract

We assess the properties of currency value strategies based on real exchange rates. We find that real exchange rates have 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) better isolates information related to the currency risk premium. In turn, the resulting measure of currency value displays considerably stronger predictive power for currency excess returns. Finally, the predictive information content in our currency value measure is distinct from that embedded in popular currency strategies, such as carry and momentum.

JEL Classification: F31, G12, G15.

Keywords: Currency value, macro fundamentals, real exchange rate, predictability.

1 Introduction

Determining the intrinsic value of a currency – in short "currency value" – is a key input into decisions of global investors. 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).[1] Real exchange rates embed expectations about future macro fundamentals and currency risk premiums, rendering them useful gauges of future currency excess returns. They also play a major 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 premiums. In essence, 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 expected future fundamentals and excess returns to obtain a more accurate measure of currency risk premiums? 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 portfolio sorts. Building portfolios to mimic the returns to a currency value investment strategy allows for a straightforward assessment of the economic significance of the link between real exchange rates, fundamentals, and currency risk premiums.

Our conceptual starting point to study the predictive power of real exchange rates and underlying drivers of risk premiums is the present-value representation of exchange rates in Section 2 (see, e.g., Engel and West, 2005, 2006; Froot and Ramadorai, 2005). From a present-value perspective, the RER is driven by i) expected excess returns (currency risk premiums), ii) the expected real interest rate differential (RID), and iii), if long-run PPP

[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).

fails to hold, the long-run expected RER. Hence, adjusting the RER for macroeconomic fundamentals related to the latter two expectations should in principle result in a cleaner measure of risk premiums. 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 economics 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 expected real interest 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 associated with RER variation is the quality of a country's exports. Differences in the quality of traded goods (i.e., a departure from the assumption of homogeneous tradable goods) will lead to persistent differences in price levels across countries such that PPP may be violated 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, we find that all four fundamentals have forecast power for real interest rate differentials. This renders them useful devices to purge the effect of fundamentals from the RER, which in turn helps obtaining a cleaner risk premium measure for investment decisions and allows for a better understanding of the information contained in the RER.

In the empirical analysis discussed in Section 3, we start by showing that 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 has become cheap in real terms compared to the dollar) have higher excess returns going forward than countries with a strong RER. Translating this predictability into 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, 2015).

The key insight of this paper is, however, that standard currency valuation metrics based on real exchange rates should be appropriately adjusted for expectations about future macro fundamentals. Purging the impact of expected fundamentals from the RER 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 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 premiums) yields a less noisy signal of what constitutes currency value. Currency risk premiums will thus be revealed with higher precision.

We conduct further analyses and provide several robustness checks related to our main results in Section 4. For example, we show in a cross-validation exercise that our main results are not driven by a particularly influential currency. Further, decomposing the information in real exchange rates into its basic components, we find that inflation differentials matter considerably as determinants of currency risk premiums. 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.[2] Also, returns of the value strategy accounting for macro

[2]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.

fundamentals are not spanned by conventional foreign exchange (FX) strategies. In fact, our proposed currency value strategy receives a higher weight in the investors' ex-post optimal portfolio allocation than a classical carry trade strategy. One may also wonder whether our results are sensitive to the particular base year chosen when 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 real exchange rates.

Taken together, these results have implications for our understanding of value in FX markets and currency risk premiums in general. Accounting for standard macro fundamentals – well-known in the international economics literature, yet hitherto unexplored in asset pricing work on exchange rates – is highly useful for strengthening the link between currency value and risk premiums. 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, which are briefly summarized in Section 5, are threefold. First, we perform an in-depth analysis of currency value strategies in a cross-sectional portfolio setting.[3] This multi-currency 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. Our results are obtained in an 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 RER models or rely on purely statistical performance criteria derived from time-series analysis of a limited number

[3]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, 2016), Lettau, Maggiori, and Weber (2014), Hassan and Mano (2015). The focus in this paper is on real exchange rates and related valuation measures which have received little attention in the recent finance literature – the exceptions being Pojarliev and Levich (2010), Asness, Moskowitz, and Pedersen (2012), Kroencke, Schindler, and Schrimpf (2014), Barroso and Santa-Clara (2015). 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 predictability of currency returns by real exchange rates, and Engel (2016) investigates the link between RER levels and (real) interest rate differentials in the time-series dimension.

of currency pairs (see, e.g., Rogoff, 1996; Sarno and M. P. Taylor, 2002; Taylor and Taylor, 2004).[4] Second, we shed light on the country-specific macroeconomic fundamentals related to currency value, allowing to better identify cross-country variation in risk premiums. This is particularly important given the work of Hassan and Mano (2015), suggesting that currency risk premiums are very persistent with greater variation in the cross-section than over time. Isolating their ultimate macro drivers is therefore key for a better understanding of currency markets. Third, while we find that standard PPP calculations provide a simple measure of currency value in our 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.

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 (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

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

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

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

where ri is the real interest rate. 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

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

The RER is thus driven by three terms: expected excess returns (which under rational expectations equate to risk premiums), expected real interest rate differentials, and the long-run expected RER. It is standard to impose $\lim_{h\to\infty} q_{t+h} = 0$. The assumption of an expected unitary RER in the very long-run (consistent with PPP) is not innocuous, however. It is well documented that there are structural and persistent differences between countries, such that even in the long-run significant violations of the standard PPP condition can arise, especially when considering emerging markets (e.g. Taylor and Taylor, 2004).

Importantly, Eq. (4) suggests that the relation of interest between the RER and (expected) currency risk premiums will also be influenced by macroeconomic fundamentals as these are the forces ultimately driving (expectations of) future real rate differentials. We thus aim at controlling for such influences to sharpen the relation between the RER and risk premiums, in turn raising the predictive power of the resulting value measure. This is the central hypothesis we take to the data in this paper.

A key question is then: what macroeconomic fundamentals can be expected to influence expectations of future real rate differentials and/or the long-run mean of the RER 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. If PPP holds, then the RER equals unity as a consequence of 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 the 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 nontradable sector tend to follow wages in the tradable sector. Thus, countries with higher productivity in the tradable sector have higher overall price levels and, hence, stronger real exchange rates as price differences in the nontradable sector cannot be eliminated by goods market arbitrage.

Exports quality. Similarly, 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 exporting higher-quality goods experience stronger RERs. An example for the relevance of the quality of exports 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 larger net external liabilities have more depreciated real exchange rates, with the main channel of transmission operating through the relative price of nontraded goods rather than risk premiums (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 four 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 currency valuation that is more closely tied to currency risk premiums.

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

3 Real exchange rates and currency risk premiums

3.1 Data

In the empirical analysis of the paper, we employ a panel of exchange rates and macro fundamentals (such as GDP, inflation, interest rates, and net foreign assets) for a long period from 1970Q1 to 2014Q1 at the quarterly frequency. Our sample covers 23 advanced economies and emerging markets. Since all exchange rates are quoted against USD, we have a total of 22 exchange rates. Most of the data are from the Global Financial Database (GFD). We also employ a measure of export quality which is obtained from the International Monetary Fund (IMF). We provide details on data sources, definition of macro fundamentals, and how we compute currency returns and real exchange rates in the Internet Appendix to this paper.

Table 1 reports descriptive statistics for excess returns (RX), (nominal) exchange rate changes (ΔS), the log RER (q), quarterly (log) RER changes (Δq), and inflation differentials ($\Delta\pi$). All quantities and growth rates are differentials (against the USD/U.S.). Specifically, we report means and volatilities for excess returns, spot exchange rate changes, real exchange rates, real exchange rate changes, and inflation differentials in our sample.[6] Average returns and exchange rate changes – as well as their volatilities – are annualized.

– Table 1 about here –

Table 1 shows that 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. For example, on the one hand, countries like Switzerland and Japan have high valuations on average (their 5-year RER changes are negative on average) as well as low inflation rates on average. On the other hand, countries such as India and

[6] We denote quarterly log RER changes as Δq in Table 1 to avoid confusion with 5-year RER changes, denoted by $\Delta^{(5y)}q_t = q_t - q_{t-5y}$, which we will use extensively in later parts of the paper.

Indonesia tend to have low valuations on average and relatively high inflation rates.

3.2 Macroeconomic fundamentals and real interest rate differentials

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

As a preliminary exercise, we run basic Granger causality-type tests to assess whether the macro variables discussed above relate to future RIDs. We do so by regressing RIDs on lagged fundamentals (and lagged RIDs) in a panel regression with time fixed effects. This specification ensures that we investigate the cross-sectional dimension of predictability, 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 variables considered have some predictive power for future RIDs. This renders them useful as control variables when purging RERs from the impact of expected fundamentals to better isolate a value signal. Interestingly, they differ in terms of the horizon over which they predict real exchange rates, though. For example, net foreign asset positions are particularly powerful at the one-year horizon, whereas output gaps work best at intermediate horizons. Judged from the strength of the statistical relationship, export quality emerges as a particularly strong driver of future RIDs, with significant predictability recorded up to the three-year horizon.

– Table 2 about here –

3.3 Accounting for macro fundamentals to better predict excess returns

Next, we go beyond the direct relation of macro fundamentals to RIDs and examine (cross-sectional) predictability of future currency excess returns. Specifically, we run panel regressions with time fixed effects of excess returns on lagged 5-year RER changes and macro fundamentals

$$RX_{j,t+1} = \alpha + \beta \Delta^{(5y)} q_{j,t} + \gamma X_{j,t} + \tau_{t+1} + u_{j,t+1}, \tag{5}$$

where β denotes the predictive slope coefficient of the value measure, X are control variables, and τ is a time fixed effect. We employ clustered standard errors (clustered by time).[7] Table 3 presents results for different specifications of this regression. As noted above, the value measure in this exercise follows the literature and is based on the 5-year (log) change in the RER level as in, e.g., Asness, Moskowitz, and Pedersen (2012), which we denote as $\Delta^{(5y)} q_t = q_t - q_{t-5y}$.[8]

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 $\Delta^{(5y)} q$ of 0.027 with a t-statistic of 2.89. These baseline results confirm 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 $\Delta^{(5y)} q$, however. Specifications (iii)-(vi) add different (lagged) macroeconomic fundamentals (one at a time) to the regression, while always controlling for RIDs as well. We find that the slope coefficient on lagged $\Delta^{(5y)} q$ increases in all cases, and that statistical significance becomes stronger as well. This effect is

[7] Since returns are close to uncorrelated, we only cluster by time here.

[8] We use 5-year changes here to make our results comparable to the earlier literature on currency value strategies and to avoid potential problems arising from non-stationarity of RER and base year effects.

especially pronounced in specification (vii) where we include all lagged macro fundamentals jointly. The slope coefficient increases to 0.039, up by 40% relative to the benchmark regression, and the t-statistic increases to 4.0. Hence, controlling for macro fundamentals enhances the predictive power of lagged long-run RER changes for future excess returns. Panel B of Table 3 shows very similar results when excluding RID from all regressions.

– Table 3 about here –

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

$$RX_{j,t+h} = \alpha_h + \beta_h \Delta^{(5y)} q_{j,t} + \gamma_h X_{j,t} + \delta_h RX_{j,t} + \tau_{t+h} + u_{j,t+h} \tag{6}$$

for forecast horizons of $h = 1, 2, ..., 20$ quarters. This regression also allows for lagged excess returns as an additional control. The sequence of estimated β_h coefficients can be thought of as the impulse-response function of excess returns to long-run 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 ($\gamma = 0$) are shown in the upper part of Figure 1, whereas the lower part of that figure shows results when controls are included. In both cases, we plot the sequence of estimated β_h coefficients and 95% confidence intervals based on clustered standard errors (clustered by time).

– 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. This allows for a direct implementation of trading strategies and to infer the economic value of the predictive relationship.

3.4 Currency value strategies

3.4.1 Constructing currency value portfolios

In our benchmark setup, we build currency portfolios with 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, i.e., $c_t = 1/\sum_j |x_{j,t} - \overline{x}_t|$. 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 weights. The portfolio return rx^p is then given by $rx^p_{t+1} = \sum_{j=1}^{N_t} w_{j,t+1} rx_{j,t+1}$. 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 components. However, due to the decomposition of the signal, the absolute amount invested in each currency for each signal can differ from the absolute amount invested for the overall signal. Hence, mean returns are not directly comparable.

In addition to the benchmark results with linear weights, we also report returns of rank portfolios (see, e.g., Asness, Moskowitz, and Pedersen, 2012), where weights are given by

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

The scaling factor c_t is analogous to the case of linear weights above (but uses ranks of signals instead of actual signals) and ensures that we are one dollar long and dollar short as in Asness, Moskowitz, and Pedersen (2012). This procedure is more conservative (in that outliers and other extreme scores of signals receive a smaller weight) and does not have the effect discussed above that the absolute amount invested changes across signals, 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) long in P_4 (weak real exchange rates) and short in P_1 (strong real exchange rates).

3.4.2 Benchmark results

We start by building benchmark value portfolios sorted on the 5-year change in the RER, $\Delta^{(5y)}q_{j,t}$. The 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 for the three different portfolio construction methods examined, and hence are of similar magnitude as in Asness, Moskowitz, and Pedersen (2012).

3.4.3 Currency value strategies accounting for macroeconomic fundamentals

We then report results for modified value strategies in Table 5 where we purge $\Delta^{(5y)}q$ of the impact of macro fundamentals, based on the intuition in Eq. (4). We do so by running *cross-sectional regressions* of value signals (5-year RER changes) on our set of four fundamentals or expected fundamentals (x_t) separately in each quarter t of our sample period

$$\Delta^{(5y)}q_{j,t} = \alpha_t + \beta_t x_{j,t} + \varepsilon^{Q}_{j,t}, \tag{9}$$

where j indexes currencies as above. This gives us a fitted value signal (which we denote by $\widehat{\Delta^{(5y)}q}$ in the following for ease of notation) and the residual value signal after stripping out the impact of (expected) fundamentals on the RER, denoted ε^q. We are mainly interested in the residual value signal, which serves as a measure of currency value when controlling for the effect of (expected) fundamentals on the RER.

We examine four different variants of this basic setup. First, we simply regress 5-year RER changes on macro fundamentals directly in each quarter. We save the fitted value of the residual 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).[9] We then run cross-sectional regressions of the value signal on these proxies for expected fundamentals

[9] 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, 2016) 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, again, sort currencies into portfolios based on either the fitted value or the residual. The third case, in Panel C, uses a simple VAR(1) of all fundamentals to compute a proxy for expected fundamentals. We estimate VARs separately for each country and recursively based on an initialization window from 1970Q1 to 1975Q4. Expected fundamentals are then obtained from iterating the VAR forward (and truncating after 20 quarters). These expected fundamentals are then used in Eq. (9) to decompose the value signal. 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 about here –

Table 5 shows annualized mean returns, t-statistics based on White (1980) standard errors, return volatilities, and Sharpe Ratios for linear (left) and rank (right) portfolios, and for a portfolio based on the 5-year change in the RER ($\Delta^{(5y)}q$), the fitted signal ($\widehat{\Delta^{(5y)}q}$), and the residual signal (ε^q). We always report returns for the benchmark value signal ($\Delta^{(5y)}q$) for comparison since including different combinations of macro variables changes the available sample period.

For all four cases in Panels A–D, we find that adjusting the RER for macro fundamentals increases the Sharpe Ratio substantially relative to the baseline case. This effect is not driven by higher mean returns but rather by lowering return volatilities.[10] This can also be seen clearly from plots of cumulative returns to rank portfolios in Figure 2 where we plot cumulative returns to the standard value strategy (based on 5-year RER changes) and cumulative returns to modified value strategies (based on ε^Q).[11] One way to interpret this finding is that purging the value signal of the impact of (expected) fundamentals results in a more precise measure of expected risk premiums, consistent with the intuition developed in

[10] Moreover, this result is true for both linear and rank portfolios. Hence it is not purely driven by investing less (in absolute terms) in the linear weight portfolios.

[11] Since controlling for expected fundamentals leads to a smaller sample size (due to the need for macro data), we compute the standard value portfolio return on the same restricted sample as the modified value strategy to make returns comparable.

Section 2.2.

– Figure 2 about here –

This effect 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 ($\Delta^{(5y)}q$) and modified value portfolios (ε^q) based on rank weights. We employ returns based on the panel VAR specification in Panel D of Table 5 in Figure 3. We compute the drawdown D_t in quarter t based on rank portfolio returns as

$$D_t = \sum_{s=1}^{t} rx_s^p - \max_{u \in \{1,\ldots,t\}} \sum_{s=1}^{u} rx_s^p \tag{10}$$

where rx^p is the portfolio excess return of the standard value portfolio (based on 5-year RER changes) or of the modified value portfolio (based on ε^q).[12] Figure 3 clearly shows that adjusting for fundamentals reduces downside risk of the currency value strategy substantially.

– Figure 3 about here –

3.4.4 Exposure to other currency risk factors

Next, we explore how the value strategies relate to other well-established common factors in currency markets. 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 (2016). 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 –

[12]This drawdown measure essentially corresponds to the cumulative return of the value portfolio relative to the last peak (Koijen, Moskowitz, Pedersen, and Vrugt, 2015) for each quarter t.

We find that the modified value strategy (ε^q) that strips out the impact of expected macro fundamentals delivers significant alphas across all specifications and even when including standard value factors 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 weight in all specifications. It even exceeds that of the classical carry trade, the currency strategy which has received most of the focus in the literature so far.[13]

4 Additional results and robustness

4.1 Macro fundamentals and real exchange rates in the cross section

To further understand the link between 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 q in our notation).

– Table 7 about here –

Except for NFA, all fundamentals enter significantly into the various regression specifications.[14] 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

[13]Weights are calculated for an ex-post tangency portfolio to show that that ex-post the efficient frontier would include the modified value strategy with a large weight. This does not necessarily imply an expansion of the ex-ante frontier but, given the large weight attributed to value, this possibility seems most likely.

[14]Note that we are again using the value signal here, i.e., the 5-year change of the RER, for consistency with our empirical analysis above. Using the RER level instead, we find that a higher NFA is associated with a higher valuation level, as one would expect.

this unexplained part is largely driven by expected excess returns (currency risk premiums).

4.2 Decomposing value signals

To shed light on the mechanics of currency value strategies and to further understand the drivers of return predictability, we further decompose the RER level into several components. Specifically, we first split the information in the log RER level (q_t) into that in the lagged 5-year RER level (q_{t-5y}) and the 5-year change in the RER $\Delta^{(5y)}q_t$.[15] 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 $\Delta^{(5y)}s_t$ and (negative) 5-year inflation differential $\Delta^{(5y)}\pi_t^*$, 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 from the RER level comes from 5-year changes in the RER, i.e., the standard value signal in this paper and the literature (Asness, Moskowitz, and Pedersen, 2012; Kroencke, Schindler, and Schrimpf, 2014; Barroso and Santa-Clara, 2015). 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.)

[15]This decomposition is akin to work in the equity market literature (e.g., Gerakos and Linnainmaa, 2016), aimed at decomposing the information content of book-to-market ratios for equity returns.

forecasts positive excess returns relative to low inflation countries. This suggests that 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. Strong currencies thus tend to earn low risk premiums going forward.

4.3 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) 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 slightly 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 small in economic terms, though. A reasonable conclusion is that value and carry capture largely unrelated dimensions of currency risk premiums.

4.4 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 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 a 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.[16] 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 that 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. The construction of this asset market home-bias measure is fairly standard (e.g., Fidora, Fratzscher, and Thimann, 2007).

Table A.I in the Internet Appendix reports results for panel regressions (with time fixed effects) where we regress our value signal on one or both of the two home bias measures, and 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 (counterintuitively) associated with a higher value signal (i.e., a weaker RER). Yet, this link is not statistically significant. Similarly, for the financial home bias measure we also find insignificant slope coefficients (specifications (iii) and (iv)). Finally, specification (v) shows that both measures are insignif-

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

icant when included jointly in the regression and when controlling for the other fundamentals. Conventional measures of home bias thus do not seem to drive the cross-sectional variation of currency value in our sample.

4.5 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, normalized to unity in 1970Q1. For robustness, we also compute portfolio returns based on a measure of the RER that is immune to the base year choice 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 these data for robustness. Table A.II in the Internet Appendix shows results for portfolios based on 5-year changes in RERs computed from absolute PPP measures and we find that the results are similar to those in Table 4.

4.6 Cross-validation: Influential currencies

To rule out the possibility that the main results are 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 strategy (ε^q) as in Table 5. The rows in Table A.III indicate which currency was excluded from the sample. Overall, we find that the results are robust and are not driven by one particular outlier currency.

4.7 Average portfolio weights

We document average rank portfolio weights in Table A.IV for all currencies in our sample. Average portfolio weights are quite similar across the four different adjustment schemes.

For example, we find that Sweden, South Korea, and Canada consistently get high positive weights across the four methods, whereas countries such as New Zealand, Hungary, Japan, and Switzerland get low weights. The table also shows that the volatility of portfolio weights is around 11% so it is not the case that our value measures always select the same currencies for going long and short, respectively.[17]

4.8 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 macroeconomic variables are reported with a lag.[18] While lagging the value signal clearly reduces mean excess returns and Sharpe Ratios for all portfolios, 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 (ε^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).

[17] The volatility of rank portfolio weights can be interpreted as a measure of portfolio turnover. However, a more intuitive way to gauge this is to use portfolio weight changes to compute actual turnover numbers. For our modified value strategy based on panel VARs, we find a quarterly turnover rate of about 21%. For comparison, turnover for a standard carry strategy is close to 10%, for momentum it is 60%, and for a standard value strategy it is about 18%.

[18] Ideally, one would want to use real-time data for this exercise, but these do not exist for our sample and set of fundamentals. Using an implementation lag of two quarters can be seen as a simple approximation.

5 Conclusion

The valuation of currencies is of key importance to international investors, but empirical evidence on the properties and determinants of "currency value" is still scattered in the literature 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 real exchange rates as well as real exchange rates adjusted for macroeconomic fundamentals for future currency excess returns. Our ultimate goal is to provide a better understanding of the link between currency valuation and risk premiums in the cross-section of currencies. We find that real exchange rates predict the cross-section of currency excess returns. A more powerful value signal can be obtained, however, when adjusting real exchange rates for key fundamentals (productivity, export quality, net foreign assets, and output gaps) – well-known from the macro exchange rate literature but hitherto unexplored in asset pricing research. Finally, portfolios based on standard and modified value signals should also be useful for research on currency risk factors in the cross-section as they offer a set of returns that are largely independent of carry and momentum.

Overall, these results are encouraging given the well-known empirical difficulties of models of exchange rate equilibrium, and should spur further research in several directions. Most importantly, while this paper has a strong empirical 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, 2016), or by extending the incomplete markets model with financial frictions of Gabaix and Maggiori (2015) to allow for additional distortions due to non-homogeneity in traded goods 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 (ΔS), the log RER (q), quarterly (log) RER changes (Δq), 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		ΔS		q		Δq		$\Delta\pi$	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
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 ΔR^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 clustered standard errors (clustered by 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	[2.89]	[3.14]	[3.41]	[3.24]	[3.22]	[3.49]	[4.00]
R^2 (%)	0.81	2.75	3.96	2.82	2.89	4.73	5.38
ΔR^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	0.039
t			[3.28]	[2.98]	[3.02]	[3.67]	[3.94]
R^2 (%)			3.01	0.81	1.04	3.86	4.72
ΔR^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 currencies that are relatively cheap and goes short currencies with valuations that have become relatively rich. Excess returns are defined such that positive numbers mean a positive return on holding the foreign currency. Mean returns, return volatilities (σ), and Sharpe Ratios (SR) are annualized. t-statistics in brackets are based on White (1980) 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	[0.73]	[0.76]	[2.38]	[4.00]	[2.71]	[3.11]	[3.15]
σ	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 ($\Delta^{(5y)}q$) and a decomposition into the part of $\Delta^{(5y)}q$ related to macro fundamentals ($\widehat{\Delta^{(5y)}q}$) and a part unrelated to these fundamentals (ε^q). We regress $\Delta^{(5y)}q$ 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 ($\widehat{\Delta^{(5y)}q}$) and the residual (ε^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 White (1980) standard errors in squared brackets, the annualized excess return volatility (σ), and annualized Sharpe Ratios (SR). The sample period is 1976Q1 – 2013Q4 (at most) and the frequency is quarterly.

	Linear portfolios			Rank portfolios		
	$\Delta^{(5y)}q$	$\widehat{\Delta^{(5y)}q}$	ε^q	$\Delta^{(5y)}q$	$\widehat{\Delta^{(5y)}q}$	ε^q
Panel A. Raw fundamentals						
mean	2.67	0.54	2.13	4.16	2.05	4.12
t	[3.35]	[0.93]	[4.91]	[3.27]	[1.47]	[4.89]
σ	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	[3.41]	[0.42]	[5.21]	[3.35]	[0.85]	[4.71]
σ	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	[3.51]	[1.24]	[4.97]	[3.46]	[1.87]	[5.32]
σ	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	[3.51]	[0.95]	[5.32]	[3.46]	[1.54]	[5.26]
σ	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). As factors in the regressions, we include excess returns to carry trades, momentum, standard value (based on 5-year RER changes, $\Delta^{(5y)}q$), and the global imbalances factor (IMB) of Della Corte, Riddiough, and Sarno (2016) 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 – 2013Q1 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 White (1980) standard errors.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)]
			Panel A. Exposure regressions			
α	4.67	4.62	2.31	4.09	3.60	2.06
	[5.26]	[4.97]	[2.92]	[4.43]	[3.75]	[2.35]
Carry		0.06	0.07		0.13	0.12
		[0.99]	[1.34]		[1.97]	[2.09]
Mom		-0.12	0.03		-0.14	0.03
		[-1.84]	[0.65]		[-2.34]	[0.52]
$\Delta^{(5y)}q$			0.45			0.44
			[8.70]			[7.48]
IMB				0.07	0.07	0.01
				[0.84]	[0.90]	[0.17]
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]
$\Delta^{(5y)}q$	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]
ε^q		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 ($\Delta^{(5y)}q_t$), the negative of 5-year inflation differentials ($-\Delta^{(5y)}\pi_t^*$), and the negative of 5-year nominal spot exchange rate changes ($-\Delta^{(5y)}s_t$). 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 and t-statistics in brackets are based on White (1980) standard errors.

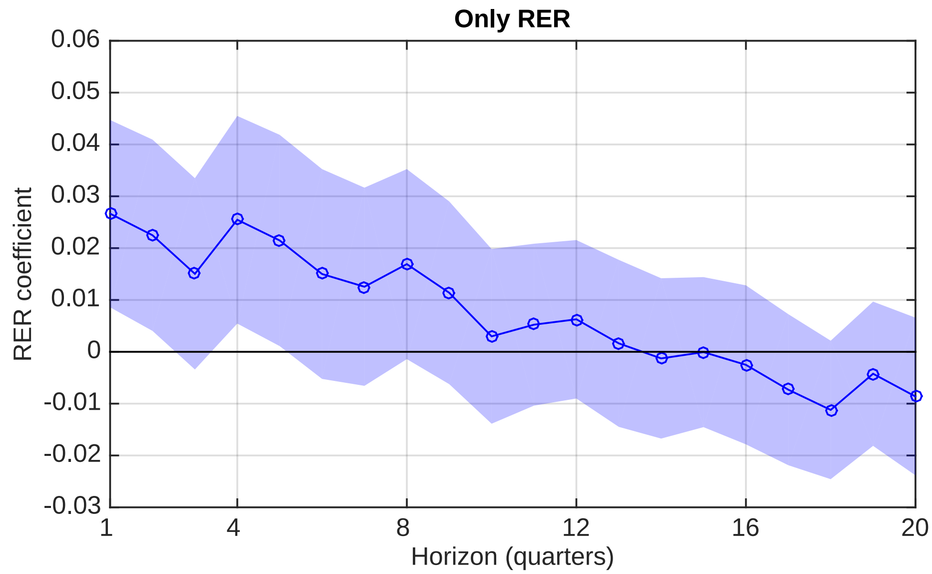
Panel A. Linear portfolios					
	q_t	q_{t-5y}	$\Delta^{(5y)}q_t$	$-\Delta^{(5y)}\pi_t^*$	$-\Delta^{(5y)}s_t$
mean	3.95	1.62	2.32	-11.74	14.07
t	[2.55]	[1.14]	[3.15]	[-4.39]	[5.01]
σ	9.59	8.83	4.57	16.59	17.41
SR	0.41	0.18	0.51	-0.71	0.81
Panel B. Rank portfolios					
	q_t	q_{t-5y}	Δq_{t-5y}	$-\Delta^*\pi_{t-5y;t}$	$-\Delta s_{t-5y;t}$
mean	2.43	1.43	3.65	-4.45	5.87
t	[1.93]	[1.07]	[3.11]	[-3.68]	[4.66]
σ	7.81	8.26	7.27	7.50	7.81
SR	0.31	0.17	0.50	-0.59	0.75

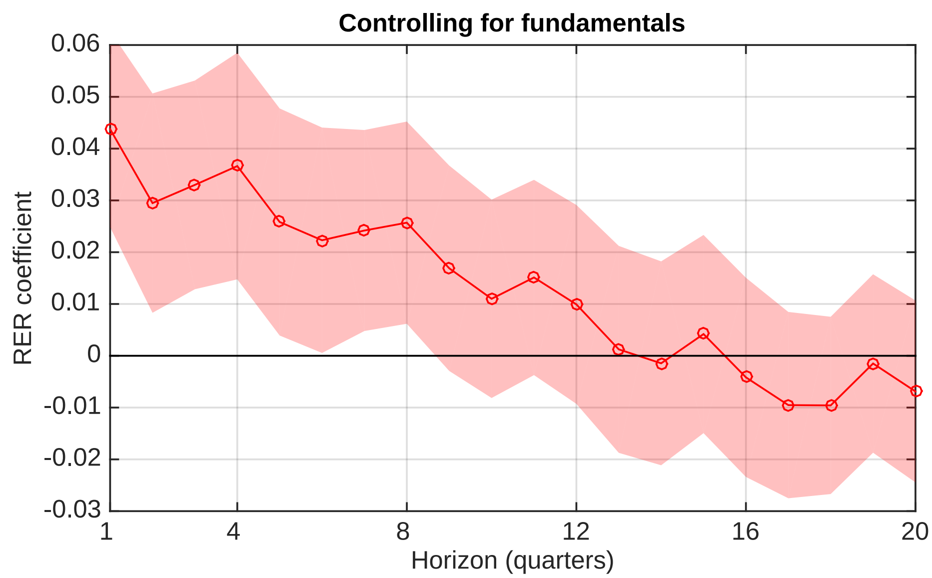
Table 9. Value vs. carry: Sequential portfolio sorts

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. t-statistics in brackets are based on White (1980) standard errors. The sample period is 1976Q1 – 2013Q4 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	[3.13]	[2.68]	[2.66]	[3.36]
σ	8.41	10.96	12.16	10.65
SR	0.53	0.46	0.45	0.57

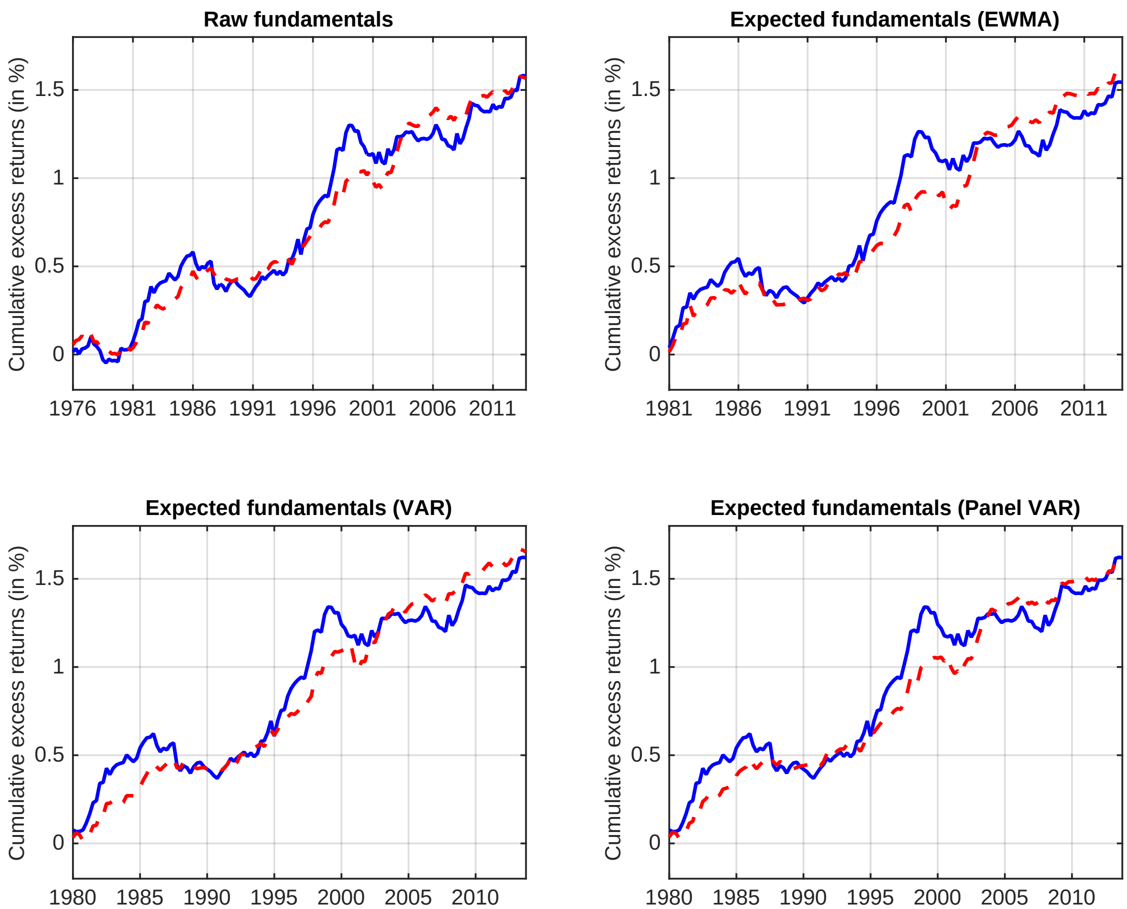
Figure 1. Impulse-response functions: Excess returns





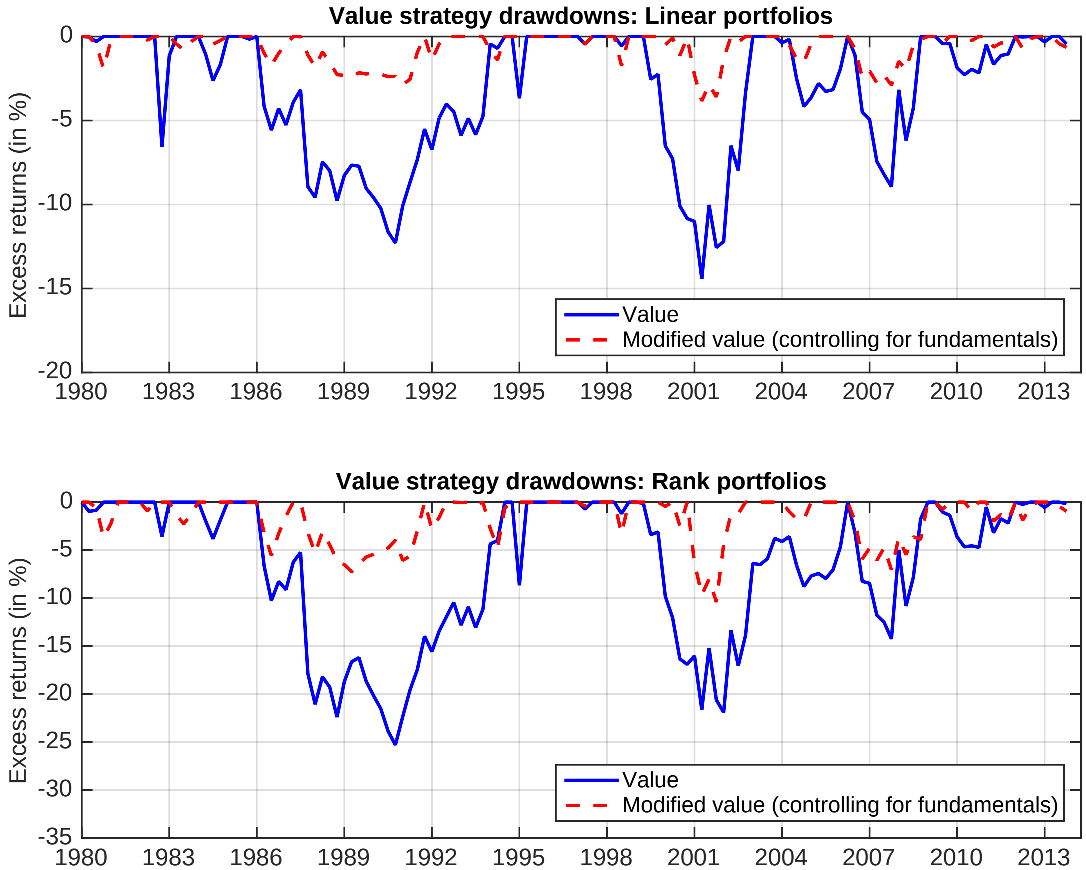
This figure plots the impulse response of excess returns to movements in 5-year RER changes. The plots are based on local projections as in Jorda (2005) and we employ panel regressions with time fixed effects to estimate the projection coefficients. Shaded areas indicate 95% confidence intervals which are based on clustered standard errors (clustered by 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 (ε^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

A. Data

A.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 a sample period starting in the first quarter of 1976, i.e. shortly after the fall of Bretton Woods.[19]

The 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 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 that 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 measures yield similar results.[20]

We collect data on a cross-section of 23 advanced economies and emerging markets. 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,

[19] 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.

[20] 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 the main analysis because of the larger cross-section, higher frequency, and because the OECD PPP rates were first constructed in the 1990s and hence would not have been available in the 1970s (the start of our sample).

Taiwan, Thailand, Turkey, United Kingdom and the United States.[21]

A.2 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 interest rates (3-month T-bills), nominal GDP, and population. Macro data 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 the analysis.[22]

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

We obtain data on the quality of export goods 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 in this area. Data on net foreign assets (NFA) are taken from Lane and Milesi-Ferretti (2007) and are updated until 2014 as in Della Corte, Riddiough, and Sarno (2016). Finally, we compute (ex-post) real interest rates (and the real interest rate differential against the USD, denoted RID) by subtracting inflation from nominal 3-month interest rates.

[21] We eliminate France, Italy, and Spain from the sample in 1999 after they adopted the Euro, only keeping Germany in the sample.

[22] Where possible, we fill in missing data in the GFD with data from Datastream.

A.3 Measuring the quality of export goods

As outlined above, the currency value measure we put forth in this paper relies on adjustments for country-specific fundamentals, most of which are fairly common in the literature and for which data are easily available. The measurement of the quality of exports, however, deserves further discussion. We use an export quality index constructed by the IMF and described in detail by Henn, Papageorgiou, and Spatafora (2013). It is constructed based on 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 production cost differences 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 constitute 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 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 is the work by Vandenbussche (2014), 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. A rigorous robustness analysis using an alternative dataset of similar quality to the IMF data is hence not possible. However, we were able to obtain the data 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 countries.[23] 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 two datasets for export quality 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 structural model.

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

A.4 Currency returns

We are interested in the returns to value strategies and currency risk premiums 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. Thus, a positive

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

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

RX indicates a positive excess return to holding foreign currency for a U.S. investor.

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

This table reports excess 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 White (1980) standard errors. The sample period is 1976 – 2013.

	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	[0.73]	[0.76]	[2.38]	[4.00]	[2.71]	[3.11]	[3.15]
std	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 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 White (1980) standard errors. The sample period is 1976Q1 – 2013Q4 (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	[4.41]	0.71	4.54	[4.39]	0.76	4.61	[4.89]	0.84	4.33	[4.75]	0.81
Canada	4.22	[4.82]	0.78	4.76	[4.53]	0.78	4.81	[5.04]	0.86	4.67	[5.02]	0.86
France	4.02	[4.67]	0.76	4.76	[4.49]	0.78	4.90	[5.39]	0.92	4.65	[5.16]	0.88
Germany	4.08	[4.55]	0.74	4.75	[4.37]	0.76	4.81	[5.01]	0.86	4.76	[5.07]	0.87
Hungary	4.15	[4.71]	0.76	4.70	[4.43]	0.76	4.90	[5.05]	0.86	4.71	[5.05]	0.86
India	4.43	[5.02]	0.81	5.02	[4.77]	0.82	5.24	[5.56]	0.95	5.02	[5.38]	0.92
Indonesia	4.14	[4.82]	0.78	4.79	[4.64]	0.80	4.84	[5.28]	0.90	4.69	[5.18]	0.88
Italy	4.48	[5.16]	0.83	5.13	[4.96]	0.86	5.19	[5.60]	0.96	5.05	[5.53]	0.94
Japan	3.86	[4.41]	0.71	4.45	[4.24]	0.73	4.74	[4.98]	0.85	4.33	[4.70]	0.80
Korea	3.40	[4.12]	0.67	4.24	[4.12]	0.71	4.08	[4.42]	0.75	3.88	[4.45]	0.76
Mexico	3.99	[4.57]	0.74	4.56	[4.70]	0.81	4.43	[4.87]	0.83	4.54	[4.92]	0.84
New Z.	4.22	[5.03]	0.81	4.93	[4.89]	0.85	4.98	[5.46]	0.93	4.77	[5.42]	0.93
Norway	4.31	[4.92]	0.80	4.88	[4.63]	0.80	5.05	[5.26]	0.90	4.90	[5.37]	0.92
Singapore	4.12	[4.89]	0.79	4.76	[4.71]	0.81	4.86	[5.32]	0.91	4.67	[5.26]	0.90
S. Africa	3.70	[4.27]	0.69	4.47	[4.30]	0.74	4.26	[4.54]	0.78	4.21	[4.62]	0.79
Spain	4.19	[4.90]	0.79	4.95	[4.72]	0.82	5.00	[5.31]	0.91	4.75	[5.20]	0.89
Sweden	4.32	[4.82]	0.78	4.99	[4.68]	0.81	5.09	[5.29]	0.90	4.93	[5.24]	0.90
Switzerland	4.20	[4.69]	0.76	4.82	[4.56]	0.79	5.03	[5.33]	0.91	4.76	[5.01]	0.86
Taiwan	4.12	[4.89]	0.79	4.76	[4.71]	0.81	4.86	[5.32]	0.91	4.67	[5.26]	0.90
Thailand	4.22	[4.69]	0.76	4.77	[4.46]	0.77	4.95	[5.27]	0.90	4.73	[4.95]	0.85
Turkey	4.05	[4.78]	0.77	4.57	[4.64]	0.80	4.89	[5.20]	0.89	4.59	[5.15]	0.88
U.K.	4.37	[4.93]	0.80	4.86	[4.57]	0.79	5.18	[5.25]	0.90	4.87	[5.19]	0.89

Table A.IV. Average rank weights

This table reports the mean and standard deviation of rank portfolio weights (in %) for the value portfolios (based on ε^q) in Table 5.

	Raw fund.		EWMA		VAR		Panel VAR	
	μ	σ	μ	σ	μ	σ	μ	σ
Australia	-1.46	10.99	-1.60	11.50	-0.09	10.23	-1.39	10.91
Canada	4.41	12.79	2.70	12.63	2.43	12.73	3.12	12.86
France	1.05	7.47	0.84	8.38	-0.07	9.12	0.64	7.84
Germany	2.69	12.28	0.87	11.81	1.40	13.11	1.56	12.47
Hungary	-6.88	10.82	-5.53	12.80	-5.58	12.04	-6.88	10.82
India	1.88	14.16	-0.75	14.08	0.37	14.26	-0.10	13.64
Indonesia	1.70	12.63	5.37	11.40	5.40	11.77	3.89	11.40
Italy	-2.52	10.29	-1.79	11.20	-2.99	10.80	-1.77	11.00
Japan	-2.93	14.36	-2.10	14.71	-2.32	14.97	-1.63	14.58
Korea	3.72	11.89	3.94	11.62	3.93	12.25	4.04	11.75
Mexico	-2.51	13.46	-3.18	13.89	-2.61	14.06	-3.12	13.98
New Z.	-4.56	12.10	-6.04	12.04	-7.04	11.46	-5.18	12.36
Norway	2.60	8.95	2.57	8.37	3.34	8.64	3.46	8.84
S. Africa	2.25	14.08	1.93	15.33	2.28	13.46	1.97	14.68
Spain	-5.54	12.59	-1.58	12.85	-2.63	12.41	-3.02	12.41
Sweden	5.96	8.01	7.11	9.02	6.39	8.51	6.12	8.30
Switzerland	-3.05	10.03	-4.55	10.45	-3.09	10.30	-3.56	10.32
Thailand	-1.62	12.91	-4.97	10.74	-4.21	11.63	-3.35	12.35
Turkey	1.74	11.97	3.71	11.60	1.52	11.99	2.20	12.12
U.K.	-0.90	13.58	0.83	12.92	0.48	12.71	0.64	13.51

Table A.V. 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		
	$\Delta^{(5y)}q$	$\widehat{\Delta^{(5y)}q}$	ε^q	$\Delta^{(5y)}q$	$\widehat{\Delta^{(5y)}q}$	ε^q
Panel A. Untransformed fundamentals						
mean	1.51	0.35	1.15	2.52	1.42	2.06
t	[1.91]	[0.56]	[2.99]	[1.83]	[0.89]	[2.41]
σ	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	[1.94]	[-0.05]	[3.45]	[1.93]	[0.75]	[3.05]
σ	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	[2.03]	[0.47]	[3.34]	[2.04]	[0.78]	[3.35]
σ	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	[2.03]	[0.43]	[3.53]	[2.04]	[0.78]	[2.77]
σ	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