Currency Risk Premia and Macro Fundamentals*

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Abstract

Macroeconomic fundamentals have substantial predictive power for exchange rates. Adopting a multi-currency portfolio perspective, we show that currency excess returns are predictable out of sample conditioning on several standard macro fundamentals, including interest rate differentials, real GDP growth, real money growth, and real exchange rates. The predictability primarily derives from variation in fundamentals across countries and much less from variation of fundamentals over time. This explains why prior work focusing on the time-series behavior of bilateral exchanges rates generally had trouble establishing a robust link between economic variables and exchange rates. We further show that currency excess returns to portfolios sorted on fundamentals can be understood by their joint exposure to dynamic business cycle risks.

JEL-Classification: F31, G12, G15.
Keywords: FX risk premium, macro risk, currency strategies, real exchange rates, carry trades.

1 Introduction

It is a common perception that fluctuations in exchange rates are random and cannot be predicted by macroeconomic fundamentals (Engel, Mark, and West, 2007). In fact, Engel and West (2005) show in a present value setting that bilateral exchange rates are basically indistinguishable from random walks when fundamentals are nonstationary and discount factors are close to one. While some success for exchange rate forecasting has been achieved at lower frequencies and longer horizons (e.g. Mark, 1995; Abhyankar, Sarno, and Valente, 2005), there is still little evidence that macro fundamentals matter for future currency returns at intermediate horizons of a quarter to a year.

In this paper, we provide encouraging new evidence suggesting that macroeconomic fundamentals do indeed have something useful to say about the behavior of currency fluctuations. We move away from traditional *time-series* forecasting of bilateral exchange rate movements, which has been the common procedure in most of the extant literature. By contrast, we rely on a portfolio approach exploiting information in the *cross-section* of countries' macro fundamentals. Moreover, we look at predictability through the lens of an international investor trying to exploit a potential link between macro fundamentals and exchange rates. Such an investor will care about currency excess returns (or risk premia) and will evaluate predictability in a multi-currency portfolio setting on the basis of economic metrics instead of standard time-series regressions.

In our empirical work, we rely on a cross-section of 35 currencies which are dynamically sorted into portfolios based on lagged macroeconomic fundamentals. The macroeconomic conditioning variables are motivated from classical exchange rate theory and include interest rate differentials (between a foreign country and the U.S.), real GDP growth differentials, real money growth differentials, and real exchange rates.

Based on this setup, we establish that macro fundamentals have significant predictive power for the future behavior of currency excess returns. The economic value of predictability is sizable. We find that following signals in our set of macro fundamentals yields unlevered excess returns of up to six percent p.a. Combining the signals of different macro fundamentals results in a currency investment strategy with a large Sharpe Ratio greater than one in annual terms.

Where does this predictability come from? To answer this question, we conduct a decomposition of the covariance between macro fundamentals and future currency returns. We find that the predictive content of fundamentals uncovered in this paper primarily originates from differences in macro fundamentals *across countries* at any given point in time. Variation in macro fundamentals *over time* for any given country, however, contributes little to predictability. These decomposition results reconcile the positive evidence regarding the link between fundamentals and currencies unveiled in this paper with those of a large prior literature that failed to establish a robust link for bilateral exchange rates. Furthermore, we show that the cross-section of excess returns to currency portfolios based on various macro fundamentals can be understood to a large degree by their common exposure to dynamic business cycle risks.

Our multi-currency portfolio approach is the key ingredient for obtaining more encouraging findings compared to the extant literature and can be motivated as follows. First, the portfolio approach comes much closer to the actions of practitioners than the isolated consideration of single exchange rates. Key players such as asset managers and hedge funds take investment decisions in a portfolio context and sophisticated hedging strategies of international trading firms also have a multi-currency focus. Second, exchange rates appear to be better predictable in pooled approaches relying on a panel of currencies rather than single exchange rates (Greenaway-McGrevy, Mark, Sul, and Wu, 2012; Mark and Sul, 2012). Third, the portfolio approach naturally delivers measures of performance, shifting the focus from a purely statistical evaluation to an assessment of the economic value of predictability.

We find empirically that countries with lower growth in real GDP (or real money balances) offer higher currency excess returns than countries with high growth in these aggregates. This finding is intuitive from a risk-based perspective where lower growth signals bad times so that investors demand a higher return as a compensation. Furthermore, high levels of exchange rate valuations (as proxied via real exchange rates) forecast lower currency returns going forward, in line with the basic message from standard real exchange rate decompositions (e.g., Froot and Ramadorai, 2005). In fact, this is the source of profitability of the foreign exchange (FX) 'value' strategy, a popular trading strategy by currency fund managers (Pojarliev and Levich, 2010).

To better understand the predictive power of these macro fundamentals, we then decompose the covariance between fundamentals and currency excess returns into various underlying drivers. This approach, recently put forth by Hassan and Mano (2013) in the context of the forward premium puzzle, allows us to dissect predictability into three components related to i) cross-sectional predictability (persistent differences in fundamentals across countries), ii) time-series predictability (variation in fundamentals over time for individual countries), and iii) predictability of movements in the U.S. dollar against a basket of all currencies. Our findings suggest that predictability mostly stems from persistent differences of fundamentals between countries but not from variation in fundamentals over time within countries or swings in the value of the U.S. dollar. This means that the predictability we uncover is more or less "static". There are persistent differences between countries, e.g., whether countries have higher or lower unconditional means of real GDP or money growth, and these persistent differences matter for future excess returns in the cross-section. Forming portfolios based on these economic variables thus captures this predictability and leads to a cross-sectional spread in returns. Variation in fundamentals over time – the focus of most of the extant literature – does not seem to matter much as a driver of currency returns.

Then, to further understand the nature of this cross-sectional predictability, we investigate whether the exposure to macro-finance risk factors can account for the spread in portfolio returns. We find this to be the case for several standard measures of business cycle risk, such as industrial production growth, and state-dependent asset pricing models involving the U.S. output gap, or the consumption-wealth ratio *cay*. These results directly relate to findings of Lustig and Verdelhan (2007) who show that returns to carry trade portfolios can be understood by their exposure to U.S. consumption growth. The robustness of a consumption-based explanation, however, has been heavily debated in the literature (see Burnside, 2011a; Lustig and Verdelhan, 2011). Drawing on our broader cross-section of currency portfolios, we find that a standard consumption growth factor does indeed do a decent (but not the best) job in capturing the cross-sectional spread in excess returns. Other measures of dynamic business cycle risk, however, are more successful and explain a large share of cross-sectional variation in excess returns of up to 90% in a cross-section of 12 portfolios. As we show via simulations, part of this success stems from power gains due to moving to a broader cross-section of FX portfolios instead of just carry trades, which reconciles the economic evidence by Lustig and Verdelhan (2007) and statistical evidence by Burnside (2011a).

The remainder of this paper is structured as follows. We discuss related literature about the fundamental determinants of exchange rates in Section 2. Section 3 informs about data and the methods used to form currency portfolios. Results on the cross-section of macroeconomic currency risk premia are provided in Section 4. Section 5 decomposes the drivers of predictability into time-series and cross-sectional components. Risk exposures of the cross-section of currency returns are examined in Section 6. Section 7 provides robustness checks, and Section 8 concludes.

2 Related Literature

Classical exchange rate theory delivers predictions on a small set of macro fundamentals that matter for the behavior of (future) exchange rates (Meese and Rogoff, 1983; Chinn, 2012). These include inflation, money, income, and short-term interest rates, among others. We take this set of fundamentals motivated by traditional theory as given but we remain agnostic with respect the validity of a specific theory. Instead, we investigate the predictive content of fundamentals for currency returns in a multi-currency portfolio setting and study the drivers of such predictability from a risk-based asset pricing perspective.

Arguably, the oldest concept of long-run exchange rate determination is purchasing power parity, or PPP (see e.g. Rogoff, 1996; Taylor and Taylor, 2004). Empirically deviations of exchange rates from PPP should be informative about future currency returns. The workhorse model of modern exchange rate theory, the (flexible-price) monetary model (e.g. Frenkel, 1976), follows a similar long-term view as PPP is assumed to hold. Specifically, price levels follow from the relative money market equilibria of the two countries concerned. The equilibrium exchange rate then depends on relative money supplies, income levels, plus further macro variables depending on the exact specification of the model. Similar exchange rate determinants feature prominently in micro-based asset-pricing models of exchange rates (Fama and Farber, 1979; Stulz, 1984). Models of this class rely on a representative agent whose utility is given by consumption and real money balances, i.e. a money-in-the-utility-function (MIUF) approach.

Some short-lived period of support notwithstanding (Frankel, 1979), it has become widely accepted since the work of Meese and Rogoff (1983) that traditional exchange rate models cannot account for exchange rate movements (Cheung, Chinn, and Garcia-Pascual, 2005). Several more recent papers, however, have made progress in establishing a link between monetary fundamentals and exchange rates. Some studies are very focused, such as Eichenbaum and Evans (1995), who find that U.S. interest rate increases (restrictive monetary policy) tend to strengthen the U.S. dollar. Other papers are more general as they examine a standard monetary model for a set of exchange rates, such as Mark (1995). However, these studies have been criticized for their lack of statistical robustness, which has motivated pooled approaches. Mark and Sul (2001) show for a panel of 19 countries that monetary fundamentals indeed have forecasting ability for exchange rates. This finding has been extended (Engel, Mark, and West, 2007) and also refined by several papers documenting the predictive ability of Taylor rule fundamentals for exchange rates (e.g. Engel and West, 2006; Mark, 2009; Molodtsova and Papell, 2009). Others remain skeptical about the robustness of such predictability (e.g. Rogoff and Stavrakeva, 2008; Engel, 2013).

In this paper, we study the relation between macroeconomic fundamentals and exchange rates via a cross-sectional portfolio approach. The application of the portfolio approach, sorting currencies according to their interest rate differentials, has been pioneered in FX analysis by Lustig and Verdelhan (2007). This has given rise to a sequence of papers which successfully rely on this approach for understanding exchange rate behavior, including Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Christiansen, Ranaldo, and Söderlind (2011), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2013), Gilmore and Hayashi (2011), Lettau, Maggiori, and Weber (2012), Lustig, Roussanov, and Verdelhan (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a,b) and Verdelhan (2013).[1] We build on this portfolio approach in our paper and show that it is useful for understanding the relation between currency returns and economic fundamentals.

3 Data and Currency Portfolios

3.1 Data Description

Our data cover a total of 36 countries (i.e., 35 exchange rates vs. the U.S. dollar) and we focus on a sample period from 1974Q1 to 2010Q3. Longer time series for many countries are available but we focus on the post-Bretton Woods period since we are mainly interested in currency returns and do not want to include periods of fixed exchange rate regimes or the short period of rapid adjustments in the immediate aftermath of the collapse of Bretton Woods.[2] We use data from 1973Q1 for some normalizations, as discussed in detail below, and even earlier data for some initializations, while

[1] This procedure is directly related to earlier studies on the forward premium puzzle. Attempts to identify exchange rate risk premia in order to understand the forward premium puzzle in single exchange rates were only met with limited success (see Engel, 1996, for a comprehensive survey of the earlier literature).

[2] Data availability varies across countries, and some countries have shorter sample periods. The 36 countries included in our sample are Argentina, Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, (South) Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom, the United States, and Venezuela.

sticking to 1974-2010 as the sample period for which we record all our out-of-sample results. The empirical analysis is based on quarterly data for exchange rates (against the USD), short-term interest rates (3-months T-Bills), real GDP, CPI inflation, and money balances ("currency in circulation") from the Global Financial Database (GFD).[3]

Since we are interested in the returns to currency portfolios conditioning on information in macro fundamentals, we compute time-series of *currency excess returns* as well as simple currency returns. Specifically, we take the viewpoint of a U.S. investor, and currency excess returns rx^j_{t+1} for a U.S. investor who holds a position in country j are computed as

$$rx^j_{t+1} = i^j_t - i_t - \Delta s^j_{t+1}, \tag{1}$$

where i^j_t denotes the (log) short-term interest rate of country j at the end of period t (for the time period from t to $t+1$), i_t denotes the (log) U.S. short-term interest rate, and Δs^j_{t+1} denotes the log change in the spot exchange rate between the U.S. and country j. The exchange rate is expressed as foreign currency units, FCU, per home currency units, USD, so that a higher exchange rate means a depreciation of the foreign currency relative to the USD. Hence, the simple exchange rate return is given by $r^j_{t+1} = -\Delta s^j_{t+1}$. We exclude the relevant European countries from the sample once they adopt the euro. We also make use of (log) real exchange rates, which are given by $\delta^j_t = s^j_t + p_t - p^j_t$, where s^j_t denotes the log exchange rate between foreign country j and the U.S., p_t denotes the level of the U.S. CPI, and p^j_t denotes the foreign country's CPI level. We normalize all countries' real exchange rates to be equal to one in 1973Q1 so that they are amenable for an out-of-sample analysis.

Finally, we make use of GDP growth differentials, money growth differentials, inflation (CPI growth) differentials between a foreign country j and the U.S. These growth differentials are based on rolling averages of growth rates over 20 quarters (i.e., 5 years). We do so to extract information about the relative state of business cycles across countries. The five-year window is long enough to smooth out short-term fluctuations but still short enough to capture movements at a business cycle

[3] GFD provides historical data for financial and macro data with long sample periods for many countries and is thus well suited for our study (e.g., Lustig and Verdelhan, 2007, also use data from GFD). In some instances, when data for a particular exchange rate or macro factor are not available, we fill the missing values based on data from Datastream or other sources but these cases are rare.

frequency.[4]

3.2 Building Currency Portfolios

We aim at identifying macro fundamentals that predict currency excess returns in the cross-section of currencies. To this end, we allocate currencies into four portfolios. First, we rank all currencies with available data according to the value of a specific macro variable (e.g., normalized real exchange rates) at the end of 1973. Next, we allocate the 25% of all currencies with the lowest values of the respective macro variable to "Portfolio 1", the next 25% to "Portfolio 2", the next 25% to "Portfolio 3", and the 25% with the highest values of the respective macro variables to "Portfolio 4". These portfolios are denoted P1 through P4. We then hold the composition of the portfolios constant for the next four quarters (1974Q1 – 1974Q4). Finally, we rebalance these four portfolios at the end of 1974 and the procedure starts again. We follow this dynamic portfolio rebalancing until the end of the sample so that we obtain four time-series of currency portfolio (excess) returns. Note that all these four portfolios are short in the U.S. dollar and long in a basket of foreign currencies by construction, i.e. taking the difference between P4 and P1 results in a dollar-neutral portfolio which is short in a basket of currencies with the lowest (lagged) values and long in a basket of currencies with the highest (lagged) values of a particular macro factor. This high-minus-low portfolio (denoted P4-P1) is especially interesting since the average return to this portfolio quantifies the economic value of currency predictability generated by a given macro fundamental.

3.3 Portfolios Conditioning on Macro Fundamentals

To examine the predictive content of different macro fundamentals, we form portfolios based on (i) interest rate differentials (as in the typical carry trade), (ii) real GDP growth, (iii) real money growth, (iv) a combination of real GDP and real money growth, (v) Taylor rule fundamentals, and (vi) real exchange rates. In the following we provide some further motivation for these variables as predictors of currency returns.

Interest rate differentials. Sorting currencies based on interest rate differentials produces a cross-

[4]Using slightly longer or shorter windows does not alter our findings reported below in a qualitative sense. Using very short windows of less than two or three years tends to matter, though. We will discuss this issue in more detail below when we decompose the covariance between fundamentals and future excess returns.

section of carry trade portfolios (Lustig and Verdelhan, 2007).[5] While carry trades are among the most heavily researched investment strategies in FX markets, so that several explanations for the profitability of carry trades already exist, we still include them in our list of portfolio sorts for two reasons. First, there is disagreement in the literature whether returns to carry trade portfolios can be understood by their exposure to standard sources of macro risk such as in a Consumption-CAPM (Lustig and Verdelhan, 2007; Burnside, 2011a). Second, carry trade portfolios form a natural benchmark for our other portfolio sorts and it therefore seems necessary to test whether portfolios sorted on other macro fundamentals capture different risks (risk premia) than carry trade portfolios.

Our first cross-section of currency excess returns is therefore based on four currency portfolios sorted on (lagged) interest rate differentials. As is well known from the earlier literature, we expect to see a higher excess return for high interest rate currencies in P4 compared to low-interest rate currencies in P1 on average.

Real GDP and money growth. In addition to carry trades, we sort currencies into portfolios based on lagged 5-year real GDP growth differentials, lagged 5-year real money growth differentials, and a combination of these two growth rate differentials. More specifically, the growth differential is the 5-year growth rate of real GDP growth (real money growth) of the foreign country minus the 5-year real GDP growth rate (real money growth) of the U.S. Real GDP growth has a natural interpretation in terms of business cycle risk and thus serves as a proxy for risks from the real side of the macroeconomy.

From a macro-finance asset pricing perspective, higher GDP growth in a country should be associated with lower marginal utility and, hence, a lower risk premium. Thus, by sorting currencies into portfolios based on lagged real GDP growth rates of the respective countries we expect to see a negative spread in excess returns in the cross-section. Low real GDP growth countries in P1 should have higher excess returns on average than high real GDP growth countries.[6] A similar reasoning applies to growth in real money balances. For example, a standard money-in-the-utility function

[5] Hansen and Hodrick (1980) and Fama (1984) showed that forward rates are biased predictors of exchange rates. This gives rise to the so-called "forward bias", that is, the empirical fact that high interest rate currencies do not depreciate enough to offset the higher interest rate *vis-a-vis* low interest rate countries. This failure of the uncovered interest parity (UIP) translates into significantly profitable "carry trades".

[6] In a recent paper, Lustig, Roussanov, and Verdelhan (2013) show that growth in U.S. industrial production forecasts currency excess returns and offer a risk-based explanation for the predictive power of this alternative business cycle proxy for currency returns. Sarno, Schneider, and Wagner (2012) also document, in a time series setting, that money growth is related to FX risk premia extracted from a multi-country term structure model.

(MIUF) delivers a pricing kernel which depends on real money growth (besides real consumption growth).[7] Money matters in this framework since investors value real money holdings for transaction purposes. Countries with lower (real) money growth should exhibit higher risk premia than countries with higher (real) money growth. The empirical prediction for our setup thus is that P1 should have higher average excess returns than P4.

Finally, since a MIUF specification contains both real money and real consumption growth, we also sort currencies into portfolios conditional on the joint signal of the two variables. For this purpose, we add real GDP and real money growth rates to obtain a single factor for univariate sorting. Two features are worth mentioning in more detail. First, we employ real GDP instead of real consumption growth although the two macro aggregates are, of course, highly but not perfectly correlated. However, GDP and consumption coincide in a Lucas (1978) tree economy so that replacing consumption by GDP does not violate this basic framework. Second, there is a long tradition in international finance to investigate the power of real output and money balances for understanding exchange rates. Our reliance on GDP instead of consumption closely resembles this tradition and makes our results more easily comparable to the traditional FX literature. Our sorts based on real GDP plus real money growth carry the same empirical prediction than the individual sorts on GDP and money growth: Countries with lower growth rates of the sum of GDP plus money balances should exhibit higher excess returns on average than countries with higher growth rates of the sum of GDP plus money balances, i.e., P1 should have higher excess returns than P4.

Taylor rule fundamentals. The recent exchange rate literature has emphasized the use of Taylor rules to capture the set of fundamentals relevant for understanding exchange rate movements (e.g., Engel and West, 2005, 2006; Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2008). Drawing on these insights, we also form portfolios based on Taylor rule fundamentals, TRF, and we employ the following simple calibration

$$\mathrm{TRF}_t = 1.5\pi_t + 0.5\widehat{y}_t \tag{2}$$

for both the home and foreign country where π denotes the inflation rate and $\widehat{y}$ denotes the percent deviation of GDP from a 5-year moving average (as a proxy for the output gap available in real-time). The calibrated parameters of 1.5 for inflation and 0.5 for the output gap are representative of what

[7] A typical money-in-the-utility function considered in the literature (see, e.g., Walsh, 2010) takes the form $U(c_{t+1}, m_{t+1}) = \frac{\left(c_{t+1}^{\alpha} m_{t+1}^{\eta}\right)^{1-\gamma}}{1-\gamma}$, where c and m denote real consumption and money, respectively, and α, η, γ are parameters of the utility function.

is often assumed in the Taylor rule literature.

Since Taylor rule fundamentals basically serve to capture the determinants of the policy rate controlled by the monetary authority, one would expect to see a similar portfolio return pattern as for carry trades sorted directly on short-term interest rates. However, we include TRF to trace out the component of interest differentials that is explained by cyclical variations in output and inflation, i.e., the part of short term rates influenced by monetary policy.

Real exchange rates. Turning to real exchange rates, one would expect that higher real exchange rates forecast higher excess returns in the future, since higher real exchange rates indicate an undervaluation of a foreign currency relative to the USD. Hence, the assumption is that PPP holds in the long run and that real exchange rates are mean-reverting to fundamental values given by PPP. This intuition is also borne out in the real exchange rate decomposition in Froot and Ramadorai (2005), which suggests that strong real exchange rates are associated with lower expected excess returns in the future. To see this, rewrite Equation (1) as

$$rx^j_{t+1} = (i^j_t - \pi^j_{t+1}) - (i_t - \pi_{t+1}) - (\delta^j_{t+1} - \delta^j_t),$$

where π^j_{t+1} denotes the log CPI change $p^j_{t+1} - p^j_t$ in the foreign country (and analogous for π_{t+1} in the U.S.), and $\delta^j_{t+1} - \delta^j_t$ is the real exchange rate change between country j and the U.S. Rearranging as $\delta_t = rx_{t+1} - (i^j_t - \pi^j_{t+1} - i_t + \pi_{t+1}) + \delta_{t+1}$, iterating forward in δ, taking conditional expectations and assuming that PPP holds in expectation in the long run ($\lim_{\ell \to \infty} \mathbb{E}_t \delta_{t+\ell} = 0$), Froot and Ramadorai (2005) obtain

$$\delta_t = \mathbb{E}_t \left[\sum_{\ell=1}^{\infty} rx_{t+\ell} - (i^j_{t+\ell-1} - \pi^j_{t+\ell} - i_{t+\ell-1} + \pi^j_{t+\ell}) \right] \tag{3}$$

which shows that higher real exchange rates today (i.e., an undervaluation relative to PPP in our quotation of exchange rates) correspond to higher expected currency excess returns going forward.

Discussion. The fundamentals discussed above represent a menu of potential economic drivers of cross-sectional variation in exchange rate returns. Our goal with these fundamentals is not to discriminate between different exchange rate theories, but to examine empirically the predictive power of alternative macro variables for future excess returns in a common setting. In other words, we take no stand on the validity of a certain theory of exchange rate determination based on our tests below, but rather attempt to shed some light on whether any or all of the above listed macro fundamentals contain predictive information about future exchange rate excess returns that is useful from an investor's (economic) perspective.

4 The Cross-Section of Macro Currency Risk Premia

Table 1 presents the results for the basic portfolio sorts where we sort currencies into quartiles conditioning on macroeconomic fundamentals. In the following, P4 denotes the portfolio which includes the currencies with the highest value of the lagged conditioning variable, whereas P1 contains the currencies which fall in the lowest quartile of the cross-sectional distribution when the portfolios are formed. The table reports the mean return on each of the quartile portfolios (in percent, per annum), the mean return on an equally weighted portfolio of the four portfolios in line with the DOL factor of (Lustig, Roussanov, and Verdelhan, 2011), and the mean return on the long-short portfolio of the extreme portfolios P4-P1.

[Insert Table 1 about here]

Carry trades. We start by discussing conventional carry trade sorts for reference purposes. As is well known (e.g. Lustig and Verdelhan, 2007), conditioning upon interest rate differentials vis à vis the U.S. produces a sizeable spread of mean returns in the currency cross-section between high interest rate currencies and low interest rate currencies. Thus, the carry trade – funding investments in high interest rate currencies by borrowing in low interest rate currencies – is highly profitable with annualized mean excess returns of a magnitude of around 6 percent p.a. in our setting.[8]

Macro fundamentals. We now turn to the novel portfolio sorts in the paper which rely on information contained in the cross-sectional dispersion of macro fundamentals across countries. To the extent that information about macro fundamentals is priced in currency markets, one should expect to see variation in expected returns across currencies which differ each point in time in terms of macro fundamentals.

We first look at the link between exchange rate returns and growth in real GDP and real money balances, as emphasized in earlier macro-based models of exchange rates (as mentioned in Section 2). As shown by Table 1, currency returns of those countries that are in the lowest quartile of the

[8]The excess return on carry trades reported in other studies is sometimes higher but we note that our portfolios are updated only annually and thus have lower turnover.

cross-sectional GDP growth distribution when building the portfolios tend to outperform those in the highest quartile by about three per cent per annum, a difference that is statistically significant at the 10% level.

More striking, currencies of countries with the lowest growth in real money balances feature returns that are about 6% higher than those with the highest growth in real money balances. This is in line with standard asset pricing reasoning, where agents derive utility from holding money in a MIUF approach. In this setting, a pricing kernel obtains where money matters for the investors' well-being. Low money growth in this conceptual framework is associated with a bad state of the economy, such that the required return for investing in the currencies of countries with low growth in real money balances is higher. Combining the information in both variables, we obtain an even higher spread in average returns, which exceeds the historical return of the carry trade (in our data).

We also sort on Taylor rule fundamentals (deviation of inflation from target and deviation of output from longer-term trend). Again, we observe a considerable spread in portfolio returns of about 3% which (albeit being more modest from an economic perspective) is statistically significant.

Finally, we turn to portfolio sorts that condition on the information in real exchange rates. This is in line with the so-called "FX value" strategy, a popular strategy among currency fund managers (e.g. Pojarliev and Levich, 2010). The FX value strategy essentially relies on the fact that PPP tends to hold in the long run but not in the short run (Taylor and Taylor, 2004). Returns on currencies whose real exchange rate appreciated most over a longer horizon may be considered as "overvalued" and are therefore likely to perform worse than investments in currencies which are "undervalued", that is those with a depressed real exchange rate over quite some time. The FX value strategy seeks to exploit this phenomenon, that is, a reversal of valuations to fundamentals. As shown by our portfolio sorts in Table 1, we indeed find this strategy to be profitable with an annualized spread in excess returns of roughly 4.5%.

Overall, these results demonstrate that macro fundamentals are informative about currency returns and exchange rates. The relations we document are reasonable from an economic point of view, contradicting the dismal evidence reported by the traditional time-series literature on the link between exchange rates and fundamentals. As we stress in this paper, the key to detect the meaningful information in macro variables for exchange rates is to investigate cross-sectional patterns (instead of a time-series approach for single individual exchange rates as emphasized in earlier research) via a cross-sectional approach.

Exchange rate changes. Table 2 repeats the portfolio sorts exercise of Table 1 but looks at simple exchange rate changes r instead of currency excess returns rx. The results for exchange rate changes largely corroborate our findings. First of all, returns to carry trade portfolios show the same increasing pattern, i.e., high interest rate currencies tend to appreciate whereas low interest rate currencies tend to depreciate. The sorts based on real GDP, real money, and the combined MIUF specification show a declining pattern in returns, similar to what we find for excess returns in Table 1, although the pattern in average returns is not always monotonically declining. However, there is no clear spread in simple currency returns for Taylor rule fundamentals, and there is an increasing pattern with a positive spread of 2.38% p.a. for real exchange rate changes; but this is not statistically significant.

[Insert Table 2 about here]

Differences between macro strategies and carry trades. How independent is the information that cross-sectional differences in macro variables convey for the behavior of currency returns from the information contained in carry trades? To study this question, we run tests where we regress the return on the long-short portfolio for the different strategies onto the carry trade long-short portfolio return – in essence the HML_{FX} factor of Lustig, Roussanov, and Verdelhan (2011). Regression results for this exercise are reported in Table 3. We find that macro-strategies based on real money and real GDP growth (MIUF) are in fact fairly unrelated to the carry trade strategy: Regression alphas are economically large and statistically significant. One interesting exception is the Taylor rule strategy, where we observe an insignificant alpha. This suggests that sorting on Taylor rule fundamentals (TRF) and interest rate differentials as in conventional carry trades is very much related. This result may not be too surprising as Taylor rule fundamentals are intended to capture the policy rate setting of the central bank, and differentials in short term interest rates are the conditioning variable in conventional carry trades. Regarding the portfolios that condition on the real exchange rate, we find that there is also some relation to carry trades, but alphas in the performance regression are still significant. Hence, real exchange rates convey information about future currency returns that goes beyond the information in interest rate differentials.

[Insert Table 3 about here]

It is also informative to assess the pairwise correlations between the returns to the macro based FX strategies. These correlations are reported in Table 4. One can observe that returns for several strategies are far from being perfectly correlated. For example, there is a relatively low correlation of only 18% between the carry and the MIUF specification. The real exchange rate strategy has a somewhat higher correlation of about 55% with the carry trade strategy but is still far below unity. The highest correlation for carry trade returns is 76% with the Taylor rule strategy returns, which is consistent with our earlier result in Table 3 that the latter strategy's returns display an insignificant alpha when projected on HML_{FX}. Strategies that condition on real money growth and real GDP growth are related to each other, but do not have much in common with the other three strategies. Moreover, carry trade and real exchange rate strategies are not perfectly correlated. These results are interesting from a portfolio diversification perspective as one would expect that a combination of these strategies should lead to sizeable gains in terms of predictability and Sharpe Ratios.

[Insert Table 4 about here]

Economic value of predictability by macro fundamentals. In the following, we take a closer look at the three most successful conditional macro FX strategies, i.e., the high-minus-low portfolios based on the carry trade (P4-P1), MIUF (where we look at the return difference between P1 and P4 because this is how an investor would implement this strategy), and real exchange rate changes (P4-P1). Results are reported in Table 5. All three zero-cost strategies are quite profitable and produce annualized Sharpe ratios in excess of 0.5, which is larger than the Sharpe ratio for the aggregate U.S. equity market. Interestingly, a strategy combining the classical carry trade, the MIUF strategy, and real exchange rate strategy in an equally-weighted portfolio generates a much higher Sharpe ratio of 1.08. A Sharpe ratio of this size for a strategy based on low-frequency macro data and annual rebalancing is remarkable. The increase in the Sharpe ratio when considering the FX strategies jointly derives from the fact that their returns do not move in lockstep such that significant performance gains can be obtained via diversification of strategies. In particular, return volatility is roughly halved by adhering to the combined macro conditioning strategy, relative to say a standard carry trade strategy. As shown further in Table 5, the strategies also differ quite substantially in terms of the skewness of their returns. The negative skewness is a well-known feature of carry trades (e.g., Brunnermeier, Nagel, and Pedersen, 2009) and we also find negative skewness for the real exchange rate strategy. However, the MIUF strategy exhibits a small *positively* skewed return distribution which is an attractive feature from an investor's perspective.

[Insert Table 5 about here]

The heterogeneous behavior of these three strategies is shown in Figure 1 which illustrates the cumulative returns of the macro FX strategies over time. It is noteworthy that the MIUF approach performed better than the carry trade in the earlier parts of the sample, however, it did not work as well as the carry trade since early 2000. Also notice the low return volatility of the combined strategy when compared to each strategy taken individually.

[Insert Figure 1 about here]

In sum, these results show that there is a link between macro fundamentals and FX markets. Macroeconomic fundamentals emphasized in standard exchange rate determination theory such as growth in real money balances, growth in real GDP and real exchange rates are associated with risk premia in the cross-section of currencies.

5 Dissecting Time-Series vs. Cross-Sectional Predictability

As a next step, we seek to understand the predictability of currency returns in our cross-sectional setting. The main question is: Why do we find predictability of exchange rate returns by macro fundamentals in the cross-section while earlier papers in the traditional literature failed to find predictability in the time-series? In other words, where does the predictability unveiled in our macro-based multi-currency investment framework come from?

5.1 Analytical Framework

To better understand the source of predictability by fundamentals, we conduct some decompositions of predictability into various components. We follow the framework put forth by Hassan and Mano (2013) and decompose the covariance between future currency returns rx_{t+1} and a given macro fundamental F_t into the sum of the expected returns in the following way

$$
\begin{aligned}
cov(rx^j_{t+1}, F^j_t) &= E((rx^j_{t+1} - \overline{rx})(F^j_t - \overline{F})) \qquad (4)\\
&= \underbrace{E(rx^j_t[\overline{F}^j - \overline{F}])}_{\text{static}} + \underbrace{E(rx^j_t[F^j_t - \overline{F}_t - (\overline{F}^j - \overline{F})])}_{\text{dynamic}} + \underbrace{E(rx^j_t[\overline{F}_t - \overline{F}])}_{\text{dollar}} + \kappa,
\end{aligned}
$$

where F^j_t denotes the macro fundamental for country j at time t, and κ is a constant. $\overline{F}$ denotes the unconditional average of the macro fundamental over time and across countries, $\overline{F}^j$ denotes the average fundamental over time for country j, $\overline{F}_t$ denotes the average fundamental across countries at time t:

$$
\overline{F} = \frac{1}{N \cdot T} \sum_{j=1}^{N} \sum_{t=1}^{T} F^j_t \qquad \overline{F}^j = \frac{1}{T} \sum_{t=1}^{T} F^j_t, \qquad \overline{F}_t = \frac{1}{N} \sum_{j=1}^{N} F^j_t.
$$

This decomposition offers an in intuitive interpretation in terms of different investment strategies (Hassan and Mano, 2013) as it basically yields three different currency portfolios. The first portfolio, with weights $[\overline{F}^j - \overline{F}]$ represents a "static" trade where the weights to currencies in the portfolio are given by the difference between the value of the average fundamental for a specific country and the average fundamental across all countries. Here, the strategy is to go long in currencies whose fundamentals have a permanently higher value than the average country and vice versa (e.g., always go long in countries which have high interest rates or high real money growth on average). Hence, this investment strategy is inherently cross-sectional in nature. The second portfolio is a "dynamic" trade with weights given by $F^j_t - \overline{F}_t - (\overline{F}^j - \overline{F})$ and the third portfolio is a "dollar" trade with portfolio weights $\overline{F}_t - \overline{F}$, i.e., the strategy is to go short USD against *all other currencies* when the cross-sectional average of the fundamental at time t is higher than the unconditional average and vice versa. Hence the sum of dynamic and dollar trades captures a purely time-series dimension, whereas the sum of static and dynamic trades capture the cross-sectional dimension of predictability (Hassan and Mano, 2013).

How is this related to our portfolio sorts? The above decomposition implies that the sum of the static and dynamic trade yields a cross-sectional trading strategy with portfolio weights $F^j_t - \overline{F}_t$, i.e., the portfolio weight of country j depends on the difference between the fundamental for country j and time t and the average fundamental across countries at time t. This trading strategy is essentially identical to our portfolios where we go long and short in currencies depending on whether their fundamental is high or low in the cross-section. Our portfolio procedure only invests in the currencies in the corner portfolios, whereas the decomposition results in portfolios which always invest in all currencies, but with different weights. However, the general principle is the same. The above decomposition also implies that the sum of the dynamic and dollar trade yields a portfolio with portfolio weights $F_t^j - \overline{F}^j$, i.e., the portfolio weight of country j depends on the country's fundamental at time t relative to its own time-series mean. Hence, a portfolio like this results in a time-series trading strategy which is akin to time-series predictability tests in the traditional exchange rate literature.

Based on this framework, we can dissect the covariance between fundamentals and future currency returns to better understand the source of predictability documented above. Do macro fundamentals have (more) predictive power in the time-series or in the cross-sectional dimension?

5.2 Where Does the Predictability Come From?

In our empirical implementation of the decomposition, we employ averages over rolling windows of 10 years (40 quarters) to estimate the "unconditional" averages. This ensures that the portfolios are investable in real time.[9] Table 6 shows results for the decomposition described above based on interest rates, real GDP growth, real money growth, the MIUF fundamental, and the real exchange rate. The first three columns show returns, t-statistics, and Sharpe Ratios for the static (Static) trade, dynamic trade (Dyn), and the dollar trade (Dol).

The key finding is that, except for the real GDP growth portfolios, it is always the static trade that shows up with the largest mean return (in absolute value) and the largest Sharpe Ratio (in absolute value). This suggests that predictability comes from persistent differences between fundamentals across countries. This is further corroborated by the cross-sectional (CS) and time-series (TS) portfolios in the next two columns. As can be seen, it is always the cross-sectional portfolio which has a significant mean return and large Sharpe Ratio (except for the real GDP growth portfolio). Hence, forecasting currency returns with macroeconomic fundamentals via our protfolio setting is not successful in a time-series setting, whereas forecasting based on cross-sectional differences (even in a static setting where differences between countries never change) yields statistically and economically significant results.

[9] Hassan and Mano (2013) also estimate unconditional averages out-of-sample to ensure investability.

Seen from this perspective, we can reconcile the positive results in this paper with the dismal findings in the extant literature that started with Meese and Rogoff (1983). While earlier papers did not find predictability of individual currency pairs in a time-series setting, we show that there is a link between fundamentals and exchange rates is the cross-section. What matters for currency return forecasting are persistent differences in fundamentals across countries ("static" trades) but less so changes in the relative fundamentals of two countries over time. This also explains why the 20-quarter average growth rates we use for the macro fundamentals better capture this sort of predictability than very short-term growth rates (like quarterly, or annually). Longer-term averages smooth out the high-frequency fluctuations in fundamentals and allow to pick up persistent differences in fundamentals across countries.

[Insert Table 6 about here]

The remaining columns in Table 6 show the correlation coefficients of the five building blocks of the decomposition (static trade, dynamic trade, dollar trade, cross-sectional portfolio, time-series portfolio) with our long-short strategies based on corner portfolios. As can be seen, the largest correlations are always found for the static trades and cross-sectional portfolios which suggests that our portfolios capture essentially the same phenomenon.

6 Risk in Macro-Based FX Strategies

We now proceed to deepen our understanding of the risk characteristics of the different FX strategies. Specifically, we ask whether currency risk premia in our macro-based cross-sections can be understood through their exposures to conventional business cycle factors. As above, we again reverse the order of the MIUF portfolios in all asset pricing tests below, so that portfolio 4 (P4) always is the high return portfolio, whereas portfolio 1 (P1) is the low return portfolio.

Preliminary analysis. We start with simple time series regressions of portfolio excess returns rx_t^i $(i = 1, ..., 12)$ onto business cycle factors. These factors are fairly standard and include the quarterly and annual growth rates of industrial production and real GDP. Moreover, we consider the two risk factors studied in Lustig and Verdelhan (2007), i.e. consumption of nondurables and services as well as durables consumption, which are originally motivated by the asset pricing model of Yogo (2006).

First of all, we examine whether the betas (or regression loadings) are statistically significant and whether there is a spread in loadings that lines up with the spread in average portfolio returns. Burnside (2011b) emphasizes that a sensible spread in betas is important to avoid concluding that a useless factor prices the assets spuriously. To test this more formally, we perform standard Wald tests, similar to Burnside (2011a). W1 tests if the loadings of the extreme portfolios are the same (that is, $H_0 : \beta_H = \beta_L$), whereas W2 tests the hypothesis that the parameters are jointly equal to zero ($H_0 : \beta_1 = \beta_2 = \ldots = \beta_N = 0$).

[Insert Table 7 about here]

Results are provided in Table 7. The standard errors take into account the conventional HAC adjustments. Starting the discussion with the Lustig and Verdelhan factors, we see that there is indeed some spread in the betas for interest rate portfolios and also for MIUF portfolios. This provides basic support for Lustig and Verdelhan's argument that currency risk premia may be understood from a consumption-based asset pricing perspective. Statistical significance of the betas is somewhat weak, however. This is underscored by the results of the two Wald tests. Results for some of the other factors, by contrast, look more promising, in particular for industrial production and real GDP growth. Several individual factor loadings are statistically significant, and one can also reject the null of equal loadings of the extreme portfolios.

[Insert Figure 2 about here]

These preliminary results provide encouraging supportive evidence for a risk-based explanation for the cross-section of FX risk premia. Currencies yielding high excess returns perform poorly during U.S. recessions. There is a clear spread in the loadings of currency returns on business cycle factors, as illustrated in Figure 2. In addition, there is evidence that the explanatory power of classical business cycle factors goes beyond the carry portfolios and also extends to the MIUF and RER sorted FX portfolios. Overall, these results provide some support for the original arguments in Lustig and Verdelhan (2007) and indicate that macro risks should not be dismissed as possible candidates for understanding the fundamentally priced risk in currency markets.

Cross-sectional asset pricing. We now present results from some fairly standard cross-sectional asset pricing tests to shed further light on which macroeconomic risk factors provide a good and parsimonious description of our currency cross-section. We focus on standard business cycle factors in linear SDF models to assess the power of key macro risk factors to account for the cross-sectional variation in currency returns. Afterwards we turn to empirical models where SDF parameters are taken to be state-dependent.

Table 8 presents the results of these asset pricing tests. The tests are based on a two-factor SDF, that includes the indicated business cycle risk factor as well as the Dollar premium factor of Lustig, Roussanov, and Verdelhan (2011). Business cycle variables such as industrial production growth and GDP growth provide a good empirical fit for our joint currency cross-section. Most successful in these tests is the annual growth rate of industrial production. Interestingly, this variable also featured prominently recently as a driver of counter-cyclical currency risk premia in the predictive regression setting of Lustig, Roussanov, and Verdelhan (2011). Other measures of output growth (in particular annual and quarterly GDP growth) also fare well in these tests.

[Insert Table 8 about here]

We now turn to tests with consumption-based asset pricing factors. The results of these tests are reported in Table 9. Panel A (i) contains results for non-durables and services consumption as in classical tests of the consumption-based model, whereas Panel A (ii) reports results for a linear factor model where we also include the growth rate of durables consumption as in Lustig and Verdelhan (2007). Interestingly, the results show that a simple consumption-based model performs surprisingly well in terms of explanatory power to account for our macro fundamentals-sorted cross-section. The factor risk price is estimated to be significantly different from zero. The benefits of adding durables consumption growth as an additional factor are fairly limited in our data.

Part of the success of the simple consumption-based model in our empirical framework likely stems from the increase in power due to moving to a broader cross-section of FX portfolios instead of just a carry portfolio cross-section. This interpretation is corroborated by a Monte Carlo study in Appendix B, which helps reconciling the economic evidence by Lustig and Verdelhan (2007) and statistical evidence by Burnside (2011a).

Accounting for state-dependence. While the unconditional models show a satisfactory performance, they still leave a large fraction of cross-sectional variation in expected returns unexplained. In the following, we thus consider linear factor models where the time-variation in parameters of the

SDF is modeled as a linear function of a lagged conditioning variable. This conditional specification of the pricing kernel gives rise to "scaled" multi-factor models in the spirit of Cochrane (1996) or Lettau and Ludvigson (2001), a class of models which allows to investigate whether risk may be better measured in conditional terms, or put differently whether returns are more positively correlated with consumption growth in periods when risk aversion and risk premia are high.[10]

[Insert Table 9 about here]

To capture state-dependency in the SDF, we first consider the consumption-wealth ratio by Lettau and Ludvigson (2001), *cay*. This variable is often considered as a proxy for time-varying risk aversion in the consumption-based asset pricing literature. Time-varying risk aversion is key in habit formation models that focus on equity markets (e.g. Campbell and Cochrane, 1999) or FX (Moore and Roche, 2008; Verdelhan, 2010).

As shown in Panel B.1 of Table 9, consumption-based models that allow the parameters of the SDF to depend on *cay* are quite successful in explaining the joint cross-section of currency risk premia with cross-sectional R^2s beyond 90%.[11] They also pass the specification test by Hansen and Jagannathan (1997). The consumption growth factor considered alone loses significance when allowing the SDF to depend on *cay*. This finding suggests that the linear consumption-based model considered here clearly benefits from allowing for time-variation in risk aversion over the business cycle. A parsimonious two-factor specification of the SDF containing the DOL factor and consumption growth interacted with *cay* (SDF specification v in Table 9) also produces very low pricing errors as depicted in Figure 3.

[Insert Figure 3 about here]

As a second specification to capture state-dependence of risk premia with the business cycle, we consider a measure of the U.S. output gap. The output gap is put forth as a measure of time-varying risk premia by Cooper and Priestley (2009), who show that this variable has good forecasting properties for equity excess returns. We compute a measure of the output gap (*gap*) by extracting the cyclical component of real GDP via the usual Hodrick and Prescott (1997) filter. We filter the

[10] For a recent survey of consumption-based asset pricing, see Ludvigson (2011).

[11] Importantly, as we pool various test assets, these tests also do not suffer from the issues outlined in Lewellen, Nagel, and Shanken (2010).

series recursively after allowing for an initialization period that precedes our post-Bretton Woods sample. Results are reported in Panel B.2 of Table 9. Similar to the previous results, we find that models relying on *gap* as a conditioning variable are quite successful in explaining the cross-section of macro currency risk premia. Particularly, the interaction term between *gap* and consumption growth exhibits strong explanatory power for the cross-section of currency risk premia. The cross-sectional R^2 reaches almost 90%, rivalling the explanatory power of the model with *cay*. These findings suggest that returns of high-yielding currency portfolios are more strongly correlated with consumption growth in recessions when risk aversion and risk premia are high.

Overall, the results of these simple asset pricing tests point towards a link between macro risk and currency markets. Models that incorporate standard macro-finance risk factors generally perform quite well in explaining currency risk premia of portfolios sorted on macro fundamentals. Additionally accounting for state-dependence goes a long way in explaining the cross-section of macro currency risk premia. Our findings thus support a risk-based explanation of exchange rate excess returns and suggest that macro risk is especially important.

7 Robustness

Other measures of "FX value". In our analysis above, we have used real exchange rates indexed to one in 1973 for each currency to implement an FX value strategy. We provide robustness on this choice by considering three alternative value measures. First, we use real exchange rates indexed to one in 2009Q4. This is obviously not useful for out-of-sample forecasting but only serves as an alternative indexing date. Second, we sort on lagged 5-year changes of real exchange rates to avoid indexing of real exchange rates at all. Third, we sort on (the negative of) lagged 5-year changes in nominal spot exchange rates. Measured this way, portfolio P4 contains currencies which have depreciated the most against the USD over the last five years whereas portfolio P1 contains the currencies that appreciated the most against the USD in the last five years.[12] We report average portfolio excess returns for these three sorts in Table A.1 of the Internet Appendix. As can be seen, all three sorts generate a significantly positive spread. A high-minus-low portfolio (P4-P1) based on the real exchange rate indexed in 2009 yields the largest annualized excess return (about 6%),

[12]This procedure is frequently used in recent work (see, e.g., Asness, Moskowitz, and Pedersen, 2012, among others) since it is known from the stock market literature that sorting on lagged 5-year returns yields equity portfolios similar to portfolios sorted on book-to-market measures (Fama and French, 1996) .

whereas high-minus-low portfolios based on 5-year real exchange rate and 5-year nominal exchange rate changes yield somewhat lower returns of roughly 3.8% and 4.3%, respectively.

Rank portfolios. In addition to our benchmark portfolio sorts, which are based on the corner portfolios or a cross-section of portfolios, we also build a zero-cost long-short portfolio based on all currencies. We follow Asness, Moskowitz, and Pedersen (2012) and form portfolios based on currencies' cross-sectional rank at each rebalancing date. More specifically, at each rebalancing date, we compute the rank rk_t^j for each currency and compute portfolio weights w_t^j according to

$$w_t^j = c_t(rk_t^j - \frac{1}{N_t}\sum_{N_t} rk_t^j)$$

where N_t is the number of currencies with available data at date t ($j = 1, 2, ..., N_t$) and the rank rk is N_t for the currency with the highest value of a signal and 1 for the currency with the lowest signal. The constant c_t serves to rescale the portfolio weights and we follow Asness, Moskowitz, and Pedersen (2012) in using two different rescaling methods: (i) we rescale the weights so that the absolute sum of all portfolio weights is equal to two, or (ii) we rescale the weights so that the ex ante expected portfolio volatility is equal to 10% p.a. The first version (i) ensures that we are one dollar long and one dollar short in the overall portfolios. The second version (ii) is based on rolling historical volatilities over the previous five years and simply serves to keep the overall volatility approximately constant over time.

We report results for both excess returns (left part) and simple spot exchange rate returns (right part) in Table A.2 in the Internet Appendix. We report results for the three signals: Interest rate differentials (carry trade, CT), real money plus real GDP growth (MIUF), and the real exchange rate (RER). Furthermore, we report results based on the overall portfolio, and on two sub-portfolios which only employ the positive and negative weights, respectively.

As can be seen from the table, we find qualitatively similar results. The three signals lead to statistically and economically significant portfolio excess returns but there is little evidence for exchange rate predictability per se. We also find that rescaling the portfolio weights to ensure an ex ante portfolio volatility of 10% (Panel B) leads to lower overall performance measures compared to the "one dollar long, one dollar short" portfolio in Panel A. Moreover, Panel A shows that the overall portfolio performance is largely driven by the investment currencies for the carry trade and real exchange rate portfolios, and largely driven by the funding currencies for the MIUF portfolios.[13]

Skipping one quarter. Since macro data are often released with some lag, we additionally skip one quarter between observing macro variables and forming portfolios. Some remarks are in order. This skipping of one quarter is not necessary for the carry trade since interest rates are observable in real time, but we still include it in this robustness exercise for completeness. Also, this modification should not have a big effect on our GDP, money, and MIUF sorts since we are sorting on 5-year growth rates which are not likely to be driven by the most recent quarter but rather capture longer-term business cycle developments. We do indeed find that our results are robust to skipping one quarter between observing the macro fundamentals and forming the portfolios, as documented in Table A.3 of the Internet Appendix.

Individual FX cross-sections. We also conduct asset pricing tests for individual FX cross-sections. Tables A.4 and A.5 of the Internet Appendix report the estimated factor risk prices separately for each of the carry, MIUF and real exchange rate cross-sections. To avoid overfitting concerns, we limit ourselves to two-factor SDF models. It is worth pointing out that an unconditional CCAPM does not perform very well on the pure carry trade cross-section (in line with, e.g. Burnside, 2011a). Nonetheless, alternative business cycle factors, e.g. industrial production growth and consumption growth scaled by *cay* tend to do a better job in terms of statistical significance and empirical fit. Overall, tests for individual exchange rate cross-sections confirm the importance of macro risk factors as drivers of currency risk premia. Statistical significance, however, is somewhat less compared to the results for the joint cross-section. As suggested by the Monte Carlo evidence in Appendix B, this likely derives from the higher power when considering the 12 portfolios jointly and estimating the model under the restriction of equal SDF parameters and risk prices across the three cross-sections.

Expanded FX cross-sections. We also perform tests on an expanded cross-section of test assets (Tables A.6 and Tables A.7 of the Internet Appendix). The test assets are six pooled sets of FX portfolios: In addition to the 12 portfolios discussed so far, we consider 4 portfolios sorted by real money growth, 4 portfolios sorted by real GDP growth, and 4 portfolios sorted by real-exchange rates based on a different base year. Thus, there is a cross-section of 24 portfolios. Again, the basic message emerges that currency risk premia are significantly linked to dynamic business cycle

[13]Note that we have not multiplied the weights for the MIUF sort by minus one here to be consistent with Table 1. In a real-world trading portfolio, the weights for the MIUF portfolio would have to be multiplied by minus one which implies that the overall portfolio return is also driven by the investment currencies and not by the funding currencies.

risk. Statistical significance is somewhat higher for the expanded cross-section of 24 FX portfolios compared to the main results for the joint cross-section of 12 portfolios, likely due to higher power of the joint tests. Conditional models perform particularly well with low pricing errors, as depicted in Figure IA.2 of the Internet Appendix.

8 Conclusion

We show in this paper that macro fundamentals contain valuable information about future exchange rate (excess) returns. This finding is in contrast to the widely-held belief that exchange rates are largely disconnected from fundamentals. However, by examining the link between macro fundamentals and exchange rate returns from a multi-currency, cross-sectional portfolio perspective, macro fundamentals appear to be informative about currency returns.

Our results show that especially short-term interest rate differentials (the 'carry trade'), real GDP growth differentials, real money growth differentials, and real exchange rates are useful for predicting exchange rate returns in a portfolio context. We find that following signals in these macro fundamentals generates unlevered excess returns of up to six percent p.a. and that combining the signals results in a strategy with a large Sharpe Ratio of more than one in annual terms. Interestingly, the macro variables found to be most useful for forecasting also feature prominently in standard exchange rate models and the uncovered forecasting relations between these fundamentals and future exchange rate returns make sense from a risk-based perspective.

We further show via decompositions that predictability of exchange rate returns by macro fundamentals is a cross-sectional rather than a time-series phenomenon. Finally, to better understand what drives the returns to our currency portfolios, we rely on an asset-pricing approach and test whether portfolios' exposure to business cycle-related risk factors can make sense of the spread in observed portfolio returns. We find that standard macro risk factors do a good job of capturing the cross-sectional patterns in portfolio excess returns in both conditional and unconditional models. These results also have strong implications for theory as they suggest to move away from two country models to multilateral approaches that fully develop the cross-sectional implications for the link of exchange rates and economic fundamentals.

References

Abhyankar, A., L. Sarno, and G. Valente (2005): "Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability," *Journal of International Economics*, 66, 325–348.

Andrews, D. W. K. (1991): "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica*, 59, 817–858.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2012): "Value and Momentum Everywhere," *Journal of Finance*, forthcoming.

Brunnermeier, M., S. Nagel, and L. Pedersen (2009): "Carry Trades and Currency Crashes," *NBER Macroeconomics Annual 2008*, 23, 313–347.

Burnside, C. (2011a): "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk: Comment," *American Economic Review*, 101, 3456–3476.

——— (2011b): "Identification and Inference in Linear Stochastic Discount Factor Models," NBER WP 16634.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2011): "Do Peso Problems Explain the Returns to the Carry Trade?," *Review of Financial Studies*, 24, 853–891.

Campbell, J. Y., and J. H. Cochrane (1999): "By Force of Habit: A Consumption Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, 107(2), 205–251.

Cheung, Y.-W., M. Chinn, and A. Garcia-Pascual (2005): "Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?," *Journal of International Money and Finance*, 24, 1150–1175.

Chinn, M. (2012): "Macro Approaches to Foreign Exchange Determination," in *Wiley Handbook of Exchange Rates*, ed. by J. James, I. Marsh, and L. Sarno. Wiley Publishing Inc.

Christiansen, C., A. Ranaldo, and P. Söderlind (2011): "The Time-Varying Systematic Risk of Carry Trade Strategies," *Journal of Financial and Quantitative Analysis*, 46, 1107–1125.

Cochrane, J. H. (1996): "A Cross-Sectional Test of an Investment-Based Asset Pricing Model," *Journal of Political Economy*, 104(3), 572–621.

——— (2005): *Asset Pricing (Revised Edition)*. Princeton University Press, NJ.

Cooper, I., and R. Priestley (2009): "Time-Varying Risk Premiums and the Output Gap," *Review of Financial Studies*, 22(7), 2801–2833.

Eichenbaum, M. S., and C. Evans (1995): "Some Empirical Evidence on the Effects of Monetary Policy Shocks on Exchange Rates," *Quarterly Journal of Economics*, 110, 975–1009.

Engel, C. (1996): "The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence," *Journal of Empirical Finance*, 3, 123–192.

——— (2013): "Exchange Rates and Interest Parity," Handbook of International Economics, Vol. 4 (forthcoming).

Engel, C., N. Mark, and K. D. West (2007): "Exchange Rate Models Are Not as Bad as You Think," *NBER Macroeconomics Annual*, 22, 381–441.

Engel, C., and K. D. West (2005): "Exchange Rates and Fundamentals," *Journal of Political Economy*, 113, 485–517.

——— (2006): "Taylor Rules and the Deutschmark-Dollar Real Exchange Rate," *Journal of Money, Credit and Banking*, 38, 1175–1994.

Fama, E., and A. Farber (1979): "Money, Bonds, and Foreign Exchange," *American Economic Review*, 69, 639–649.

Fama, E. F. (1984): "Forward and Spot Exchange Rates," *Journal of Monetary Economics*, 14, 319–338.

Fama, E. F., and K. R. French (1996): "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance*, 51, 55–84.

Farhi, E., S. P. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan (2013): "Crash Risk in Currency Markets," Working Paper, MIT Sloan.

Frankel, J. A. (1979): "On the Mark: A Theory of Floating Exchange Rates Based on Real Interest Differentials," *American Economic Review*, 69, 610–622.

Frenkel, J. A. (1976): "A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence," *Scandinavian Journal of Economics*, 78, 200–224.

Froot, K. A., and T. Ramadorai (2005): "Currency Returns, Intrinsic Value, and Institutional-Investor Flows," *Journal of Finance*, 60, 1535–1566.

Gilmore, S., and F. Hayashi (2011): "Emerging Market Currency Excess Returns," *American Economic Journal: Macroeconomics*, 3, 85–111.

Greenaway-McGrevy, R., N. C. Mark, D. Sul, and J. Wu (2012): "Exchange Rates as Exchange Rate Common Factors," Working Paper, Notre Dame.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50(4), 1029–1054.

Hansen, L. P., and R. J. Hodrick (1980): "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis," *Journal of Political Economy*, 88(5), 829–853.

Hansen, L. P., and R. Jagannathan (1997): "Assessing Specification Errors in Stochastic Discount Factor Models," *Journal of Finance*, 52(2), 557–590.

Hassan, T., and R. Mano (2013): "Forward and Spot Exchange Rates in a Multi-Currency World," *Working Paper, Chicago Booth*.

Hodrick, R., and E. C. Prescott (1997): "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29, 1–16.

Jagannathan, R., and Z. Wang (1996): "The Conditional CAPM and the Cross-Section of Expected Returns," *Journal of Finance*, 51(1), 3–53.

Lettau, M., and S. Ludvigson (2001): "Ressurrecting the (C)CAPM: A Cross-Sectional Test when Risk Premia Are Time-Varying," *Journal of Political Economy*, 109, 1238–1287.

Lettau, M., M. Maggiori, and M. Weber (2012): "Conditional Currency Risk Premia," Working Paper, Berkeley and NYU.

Lewellen, J., S. Nagel, and J. Shanken (2010): "A Skeptical Appraisal of Asset Pricing Tests," *Journal of Financial Economics*, 96, 175–194.

Lucas, Jr., R. E. (1978): "Asset Prices in an Exchange Economy," *Econometrica*, 46, 1426–1445.

Ludvigson, S. C. (2011): "Advances in Consumption-Based Asset Pricing: Empirical Tests," NBER Working Paper 16810.

Lustig, H., N. Roussanov, and A. Verdelhan (2011): "Common Risk Factors in Currency Markets," *Review of Financial Studies*, 24, 3731–3777.

Lustig, H., N. L. Roussanov, and A. Verdelhan (2013): "Countercyclical Currency Risk Premia," *Journal of Financial Economcis*, forthcoming.

Lustig, H., and A. Verdelhan (2007): "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk," *American Economic Review*, 97, 89–117.

——— (2011): "The Cross-Section of Foreign Currency Risk Premia and Consumption Growth Risk: Reply," *American Economic Review*, 101, 3477–3500.

Mark, N. C. (1995): "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability," *The American Economic Review*, 85, 201–218.

——— (2009): "Changing Monetary Policy Rules, Learning, and Real Exchange Rate Dynamics," *Journal of Money, Credit and Banking*, 41, 1047–1070.

Mark, N. C., and D. Sul (2001): "Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post-Bretton Woods Sample," *Journal of International Economics*, 53, 29–52.

——— (2012): "When Are Pooled Panel-Data Regression Forecasts of Exchange Rates More Accurate than the Time-Series Regression Forecasts?," in *Wiley Handbook of Exchange Rates*, ed. by J. James, I. Marsh, and L. Sarno. Wiley Publishing Inc.

Meese, R. A., and K. Rogoff (1983): "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?," *Journal of International Economics*, 14, 3–24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a): "Carry Trades and Global Foreign Exchange Volatility," *Journal of Finance*, 67, 681–718.

——— (2012b): "Currency Momentum Strategies," *Journal of Financial Economics*, 106, 660–684.

Molodtsova, T., A. Nikolsko-Rzhevskyy, and D. H. Papell (2008): "Taylor Rules with Real-time Data: A Tale of Two Countries and One Exchange Rate," *Journal of Monetary Economics*, 55, S63–S79.

Molodtsova, T., and D. Papell (2009): "Out-of-sample Exchange Rate Predictability with Taylor Rule Fundamentals," *Journal of International Economics*, 77, 167–180.

Moore, M., and M. Roche (2008): "Volatile and Persistent Real Exchange Rates with or without Sticky Prices," *Journal of Monetary Economics*, 55, 423–433.

Newey, W. K., and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

Parker, J. A., and C. Julliard (2005): "Consumption Risk and the Cross Section of Expected Returns," *Journal of Political Economy*, 113, 185–222.

Pojarliev, M., and R. M. Levich (2010): "Trades of the Living Dead: Style Differences, Style Persistence and Performance of Currency Fund Managers," *Journal of International Money and Finance*, 29, 1752–1775.

Rogoff, K. (1996): "The Purchasing Power Parity Puzzle," *Journal of Economic Literature*, 34, 647–668.

Rogoff, K., and V. Stavrakeva (2008): "The Continuing Puzzle of Short Horizon Exchange Rate Forecasting," NBER Working Paper No. 14071.

Sarno, L., P. Schneider, and C. Wagner (2012): "Properties of Foreign Exchange Risk Premia," *Journal of Financial Economics*, 105, 279–310.

Stulz, R. (1984): "Currency Preferences, Purchasing Power Risks, and the Determination of Exchange Rates in an Optimizing Model," *Journal of Money, Credit, and Banking*, 16, 302–316.

Taylor, A., and M. Taylor (2004): "The Purchasing Power Debate," *Journal of Economic Perspectives*, 18, 135–158.

Verdelhan, A. (2010): "A Habit-Based Explanation of the Exchange Rate Risk Premium," *Journal of Finance*, 65, 123–145.

——— (2013): "The Share of Systematic Risk in Bilateral Exchange Rates," Working Paper, MIT Sloan.

Walsh, C. E. (2010): *Monetary Theory and Policy*. MIT Press.

Yogo, M. (2006): "A Consumption-Based Explanation of Expected Stock Returns," *Journal of Finance*, 61(2), 539–580.

A Asset Pricing Tests: Methods

To investigate the macro risk premia that are priced in currency markets, we make use of some fairly standard cross-sectional asset pricing tests. According to the fundamental asset pricing equation, risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$\mathbb{E}[\psi_{t+1} rx^i_{t+1}] = 0, \qquad (i = 1, ..., N). \tag{A.1}$$

Our asset pricing tests rely on an SDF linear in the factors h_t

$$\psi_t = 1 - b'(h_t - \mu_h), \tag{A.2}$$

where b is the vector of SDF parameters and μ_h denotes the means of the macro risk factors. The setup corresponds to the so-called M-normalization of the SDF considered in **?** who shows analytically and via simulations that the M-normalization makes it less likely to conclude that a spurious factor prices the assets in finite samples. Eq. (A.1) implies a beta pricing model where expected excess returns depend on factor risk prices λ and risk quantities β_i (regression loadings of portfolio excess returns on the risk factors):

$$\mathbb{E}\left[rx^i\right] = \lambda'\beta_i \tag{A.3}$$

for each asset i (see e.g. Cochrane, 2005). The relationship between the factor risk prices in Eq. (A.3) and the SDF parameters in Eq. (A.1) is given by $\lambda = \Sigma_h b$, where $\Sigma_h = \mathbb{E}(h_t - \mu_h)(h_t - \mu_h)'$ is the covariance matrix of factors.

We estimate model parameters via the generalized method of moments (GMM) of Hansen (1982). Estimation draws on a pre-specified weighting matrix (identity matrix) with unconditional moments. We report estimates of b and implied factor prices λs as well as cross-sectional R^2s and the Hansen-Jagannathan (HJ) distance measure (Hansen and Jagannathan, 1997). Standard errors are based on Newey and West (1987) with optimal lag length selection according to Andrews (1991). We also report simulated p-values for the test of whether the HJ distance is equal to zero. Simulations are based on weighted $\chi^2(1)$-distributed random variables (for more details on the computation of the HJ distance and the respective tests (see e.g. Jagannathan and Wang, 1996; Parker and Julliard, 2005).

B Small-sample Properties of Asset Pricing Tests

In this section, we analyze the properties of the asset pricing test procedures in finite samples. We are particularly interested in better understanding the impact of the cross-sectional dimension N of the test asset returns on the quantitative conclusions of whether macro risk is priced in currency markets. In other words, do the tests have greater power when the cross-sectional dimension N is increased in the SDF/GMM setting?

To understand the small sample properties better, we run Monte Carlo experiments where we generate artificial samples of currency portfolio returns and factors. In these experiments, whose design closely follows Burnside (2011b), the factors price the asset returns by construction. We calibrate the Monte Carlo simulation to our empirical setup with currency portfolios and the macro risk factors. Based on the simulated data from the model, we are then in a position to assess the small-sample properties of the conventional asset pricing tests and evaluation metrics.

The Data Generating Process. We simulate artificial data from a two-factor asset pricing model with the SDF given by $\psi_t = \tilde{a} - \tilde{b}' h_t$. In our simulations, we set the SDF parameters to $\tilde{a} = 1.1$ and $\tilde{b} = (\,0.015 \quad 1.78\,)'$. The dynamics of the factors are modeled as $h_t \sim Niid(\mu_h, \Sigma_h)$, where μ_h and Σ_h are set equal to the sample mean and the covariance matrix of the DOL and Δc factors over the sample period analyzed in the paper. This implies the following true parameters under the M-normalization $b = (\,0.044 \quad 5.226\,)'$ and $\lambda = (\,0.330 \quad 0.986\,)'$. We simulate a $N \times 1$ vector of test asset returns rx_t

$$rx_t = \mu_r + \beta(h_t - \mu_h) + \Psi \xi_t, \tag{A.4}$$

where β is a $N \times K$ matrix collecting factor loadings, μ_r is a $N \times 1$ vector and Ψ_t is a lower triangular matrix. The return innovations are modeled as $\xi_t \sim Niid(0, I_N)$. The covariance matrix of returns is thus given as $\Sigma_r = \beta \Sigma_h \beta' + \Psi \Psi'$ and we set it equal to the sample return covariance matrix in our currency portfolio cross-section. To ensure that expected returns under the model are quantitatively equivalent to those in the data, we set μ_r equal to $\beta \Sigma_h b / (a - \mu_h' \tilde{b})$. In this setup, the model prices the asset returns by construction. We simulate artificial samples of different length $T = 100, 150, 200, 500, 1,000, 5,000, 10,000$. The empirically relevant case is T=150, which is slightly higher than the 144 quarterly observations in our quarterly post-Bretton Woods sample. The number of draws in the Monte Carlo experiment is set to 10,000.

Monte Carlo Results. The results of the Monte Carlo experiments are reported in Table A.9. Panel A reports results when the asset pricing model is estimated on a small cross-section of test assets ($N = 4$), calibrated to our carry trade portfolios. Panel B shows results of the Monte Carlo experiment when the asset pricing model is estimated on the larger $N = 12$ cross-section, calibrated to the joint CT, RER and MIUF portfolios. The first pricing factor in these tests mimics the empirical properties of the DOL factor whereas the second factor mimics the properties of the consumption growth factor.

The first interesting observation concerns the bias of parameters, which can be fairly large in small samples. For $T = 100$ and $N = 4$, for instance, the factor risk price of the artificial consumption growth factor (λ_2) exhibits a substantial downward bias of about 56%. This bias tends to be slightly higher for the larger cross-section ($N = 4$) and only becomes negligible for large samples of about 1,000 observations and more. Moreover, the test of overidentifying restrictions, typically referred to as J_T-test, exhibits some severe size distortions in finite samples.[14] In our simulations from the true model with a small cross-section and representative sample size ($N = 4, T = 150$), we observe a rejection rate greater than 10% for an asymptotic 5%-level test. As the cross-sectional dimension increases $N = 12, T = 150$, the J_T test grossly over-rejects with a rejection rate of more than 50% for an asymptotic 5% level test. Only in very large samples of 10,000 observations and more does the size of the J_T-test converge to the correct size. This implies that the empirical rejection of an asset pricing model by the J_T-test in typical samples used by empirical researchers has fairly little to say about the quality of a specific macro-finance asset pricing model.

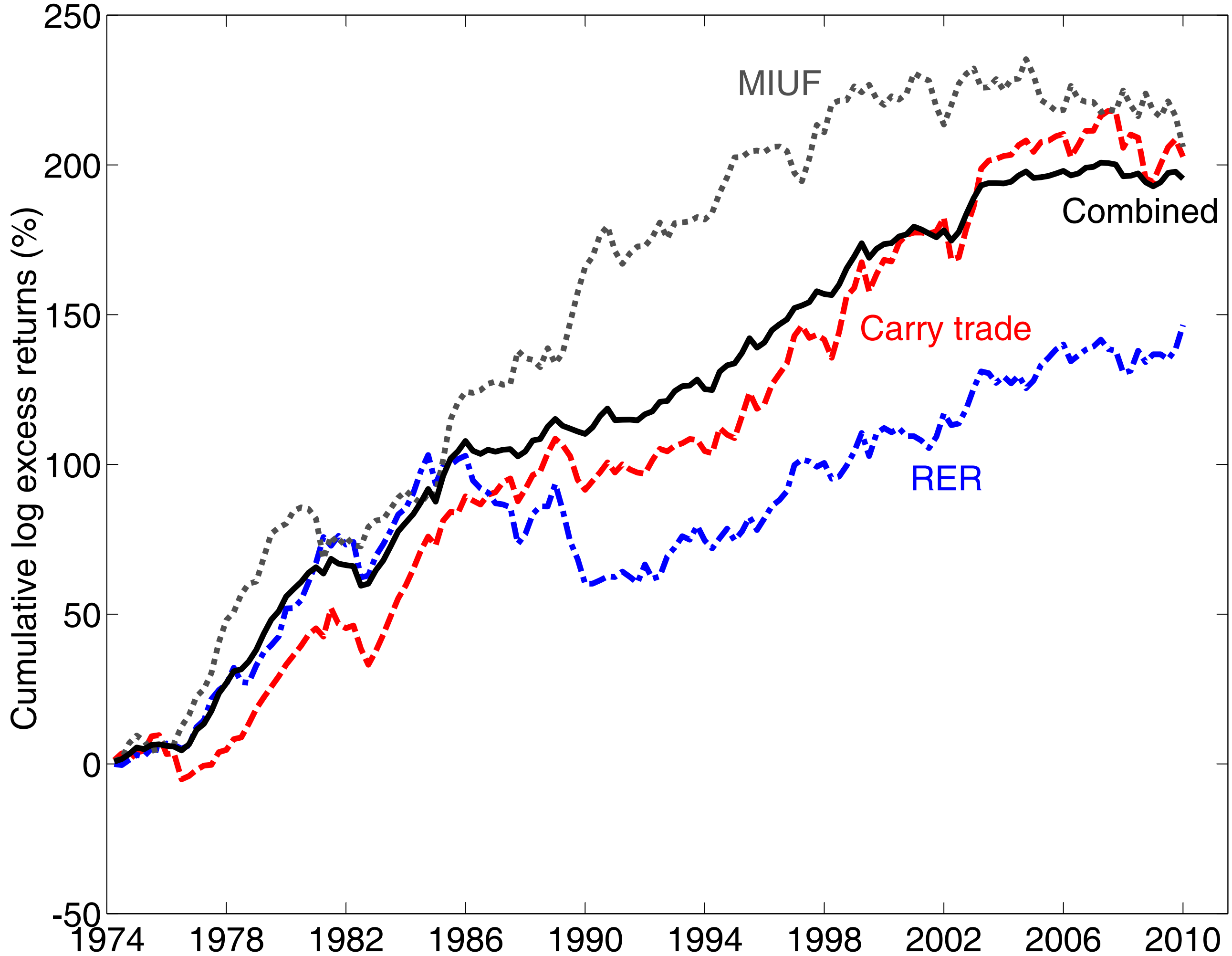
[Insert A.9 about here]

Most interestingly, however, is how the power of the tests of the factor risk prices and SDF parameters is affected as the model is estimated either on a small ($N = 4$) or a large ($N = 12$) cross-section of test assets. Concentrating on the $T = 150$ case which comes close to the sample size in our

[14]The null hypothesis of the J_T test is that the empirical moments are jointly equal to zero, or in other words, that the asset pricing model is true. By contrast, t-tests of the SDF parameters or factor price test the null that the factor does not price the test assets, i.e. that the asset pricing model does not hold.

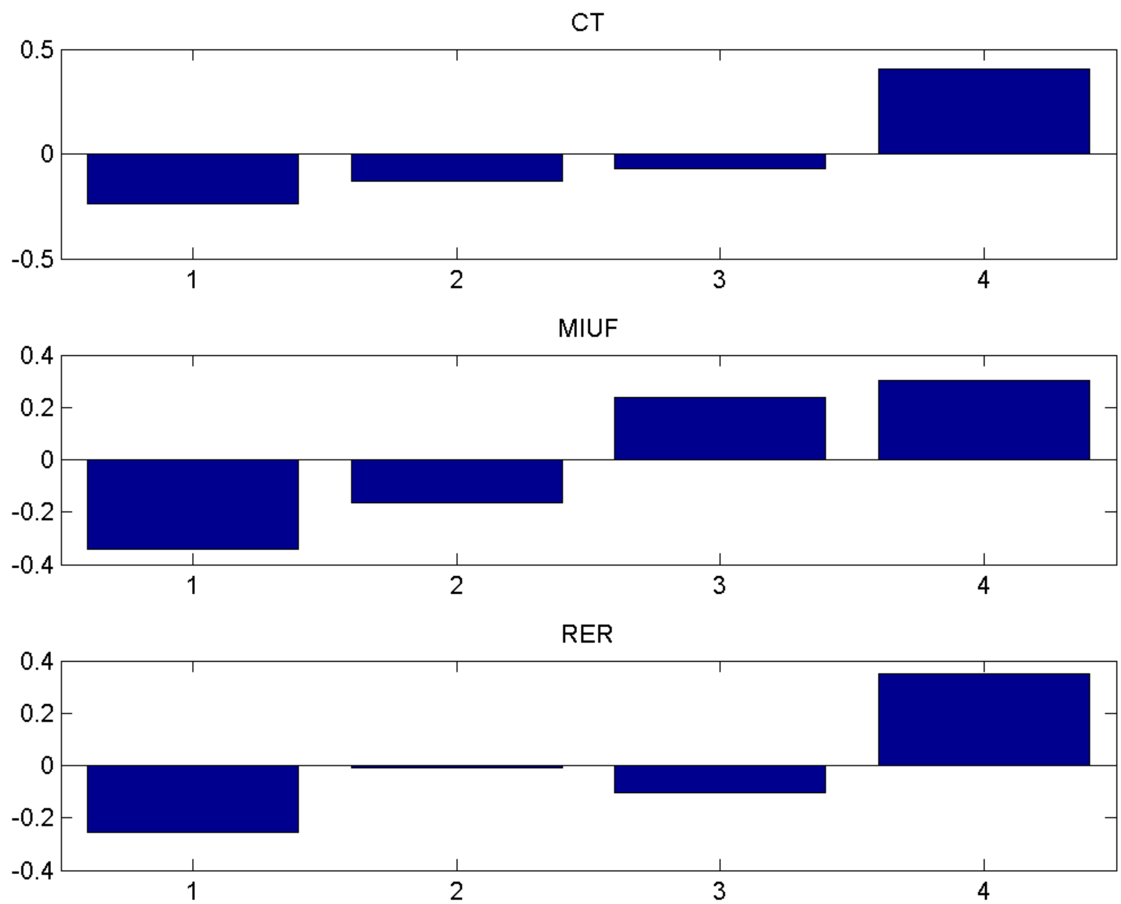
empirical study, we see that the power of the conventional tests can be fairly low if the cross-sectional dimension is low. Estimating the model on a small cross-section ($N = 4$), the researcher would only conclude in about 20% of the cases that the factor prices the assets based on an asymptotic t-test (5%-level) for the SDF parameter b_2 or the factor risk price λ_2. Not surprisingly, the power of these tests approaches 100% as the sample size gets very large. Importantly, however, making no full use of the cross-sectional of test asset returns implies a substantial loss in power in finite samples. If the model is estimated on the full cross-section $N = 12$, one would (correctly) conclude that the artificial consumption factor prices the assets in about 80% of the cases based on 5%-level tests for b_2 and λ_2. Thus, increasing the cross-sectional dimension as we do in our empirical analysis in the main text, likely increases the power of our tests with macroeconomic risk factors.

Figure 1. Cumulative Returns



The figure shows cumulative log returns for three trading strategies based on the carry trade (P4 minus P1), the real exchange rate (base year 1973, P4 minus P1), real money plus real GDP growth (P1 minus P4), and a combination of the three strategies (average return across the former three strategies).

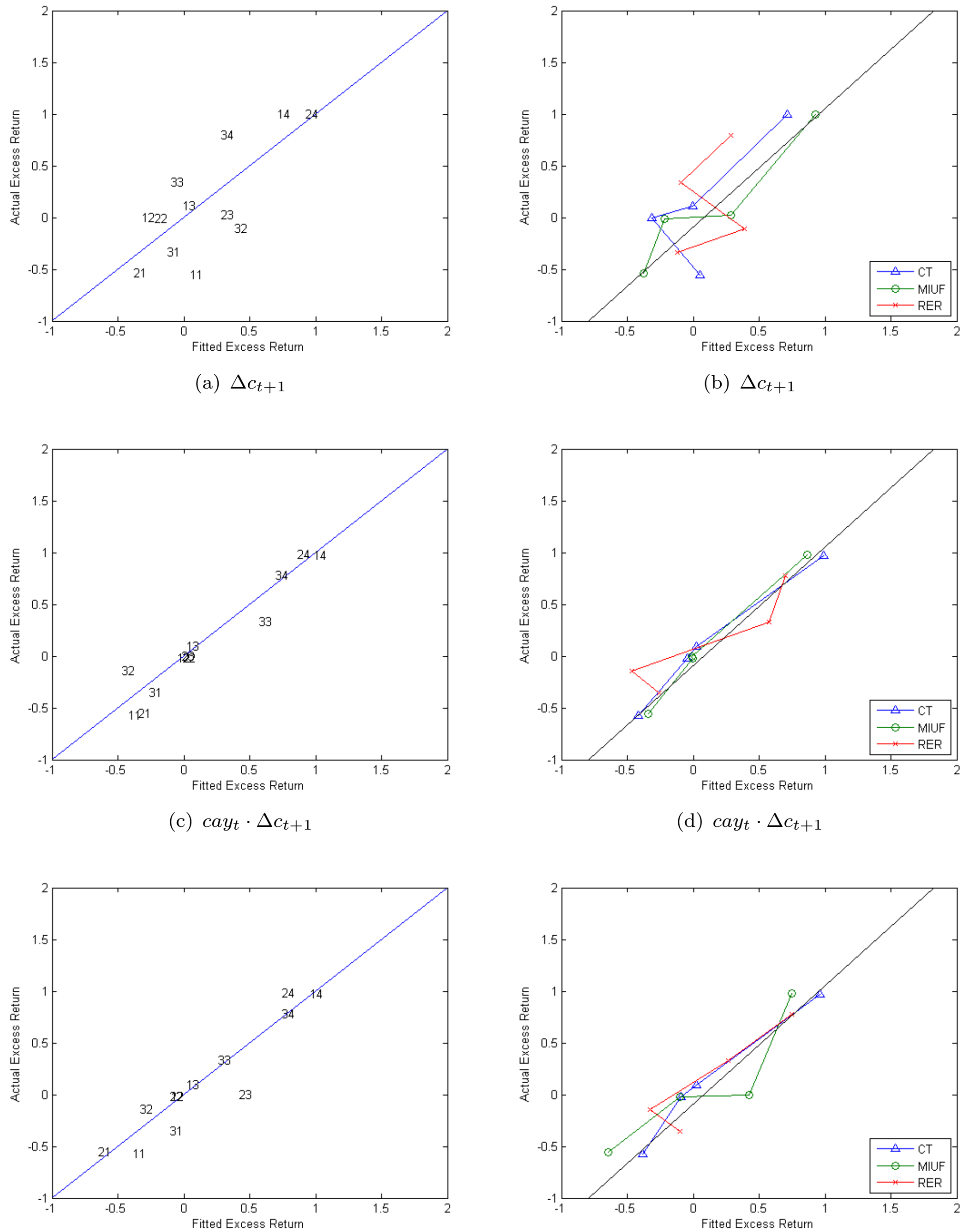
Figure 2. Business Cycle Sensitivity of FX Portfolios



(a) Industrial Production Growth (YoY)

The Figure shows loadings of FX portfolio returns on the annual growth rate of industrial production (YoY), obtained via time-series regressions. The test assets are 3 groups of FX portfolios that are pooled together in the tests: Portfolios 11 to 14 are sorted according to interest rate differentials (CT), portfolios 21-24 are sorted by real money and GDP growth (MIUF), and portfolios 31 to 34 are based on sorts by real-exchange rates (RER), i.e. there are 12 portfolios included. The data are quarterly and span the period: 1974Q1–2010Q3.

Figure 3. Pricing Error Plots



(a) Δc_{t+1} (b) Δc_{t+1}

(c) $cay_t \cdot \Delta c_{t+1}$ (d) $cay_t \cdot \Delta c_{t+1}$

(e) $gap_t \cdot \Delta c_{t+1}$ (f) $gap_t \cdot \Delta c_{t+1}$

The Figure shows selected pricing error plots for unconditional and scaled versions of consumption-based asset pricing models. The test assets are 3 groups of FX portfolios pooled together: Portfolios 11 to 14 are sorted according to interest rate differentials (CT), portfolios 21-24 are sorted by real money and GDP growth (MIUF), and portfolios 31 to 34 are based on sorts by real-exchange rates (RER), i.e. there are 12 portfolios. The graphs are based on GMM estimation of corresponding specification of a two-factor SDF which includes the DOL factor and the indicated factor. The right hand graphs show plots where, for each group, the solid lines connect portfolios from low to high values of the sorting characteristic. The data are quarterly and span the period: 1974Q1-2010Q3.

Table 1. Macro Fundamentals and FX Portfolio Returns

Portfolio mean excess returns from P1 (low values) to P4 (high values) based on the country characteristics indicated in the heading of each table section. "Av." denotes the average of all four portfolios and "P4-P1" is a (zero-cost) high minus low portfolio. HAC t-stats with Newey and West (1987) correction in brackets. The sample period is 1974Q1–2010Q3.

	P1	P2	P3	P4	Av.	P4-P1
A. Carry Trade (CT)						
Mean	-2.11	0.05	0.43	3.99	0.59	6.10
t-stat	[-1.53]	[0.04]	[0.28]	[2.20]	[0.45]	[3.78]
B. Real GDP growth						
Mean	2.10	1.01	0.51	-1.20	0.60	-3.31
t-stat	[1.46]	[0.63]	[0.34]	[-0.73]	[0.46]	[-1.91]
C. Real money growth						
Mean	4.32	-0.02	-0.48	-1.64	0.54	-5.96
t-stat	[2.30]	[-0.01]	[-0.38]	[-1.27]	[0.41]	[-3.59]
D. Real GDP growth + real money growth						
Mean	4.07	0.15	-0.05	-2.14	0.51	-6.22
t-stat	[2.15]	[0.10]	[-0.04]	[-1.44]	[0.39]	[-3.39]
E. Taylor rule fundamentals						
Mean	-0.65	1.33	-0.18	2.36	0.72	3.01
t-stat	[-0.46]	[1.12]	[-0.17]	[1.48]	[0.62]	[1.97]
F. Real exchange rate (base year 1973)						
Mean	-1.30	-0.42	1.40	3.17	0.72	4.47
t-stat	[-0.94]	[-0.29]	[1.08]	[2.21]	[0.63]	[2.82]

Table 2. Macro Fundamentals and FX Portfolios: Exchange Rate Changes

Portfolio mean excess returns from P1 (low values) to P4 (high values) based on the country characteristics indicated in the heading of each table section. "Av." denotes the average of all four portfolios and "P4-P1" is a (zero-cost) high minus low portfolio. HAC t-stats with Newey and West (1987) correction in brackets. The sample period is 1974Q1–2010Q3.

	P1	P2	P3	P4	Av.	P4-P1
A. Carry Trade (CT)						
Mean	-2.11	0.05	0.43	0.89	-0.18	3.01
t-stat	[-1.53]	[0.04]	[0.28]	[0.43]	[-0.13]	[1.66]
B. Real GDP growth						
Mean	0.24	0.13	0.39	-1.45	-0.17	-1.69
t-stat	[0.15]	[0.07]	[0.26]	[-0.88]	[-0.12]	[-0.90]
C. Real money growth						
Mean	1.34	-0.02	-0.61	-1.64	-0.23	-2.98
t-stat	[0.64]	[-0.01]	[-0.48]	[-1.27]	[-0.17]	[-1.65]
D. Real GDP growth + real money growth						
Mean	2.16	-0.88	-0.05	-2.29	-0.27	-4.45
t-stat	[1.11]	[-0.55]	[-0.04]	[-1.54]	[-0.19]	[-2.39]
E. Taylor rule fundamentals						
Mean	-0.50	1.14	-0.68	-0.73	-0.19	-0.24
t-stat	[-0.32]	[0.83]	[-0.50]	[-0.38]	[-0.14]	[-0.15]
F. Real exchange rate (base year 1973)						
Mean	-1.01	-0.37	-1.16	1.38	-0.29	2.38
t-stat	[-0.63]	[-0.23]	[-0.70]	[0.93]	[-0.21]	[1.62]

Table 3. Macro Fundamentals and FX Portfolio Returns: Adjusted Excess Returns

Adjusted excess returns for P1 to P4 based on the alphas in regressions of individual portfolio excess returns on the excess return to the carry trade shown in Table 1 above. "Av." denotes the average of all four portfolios and "P4-P1" is a (zero-cost) high minus low portfolio. HAC t-stats with Newey and West (1987) correction in brackets. The sample period is 1974Q1–2010Q3.

	P1	P2	P3	P4	Av.	P4-P1
A. Carry Trade (CT)						
Mean	-0.76	0.49	0.70	-0.76	-0.09	
t-stat	[-0.56]	[0.34]	[0.42]	[-0.56]	[-0.06]	
B. Real GDP growth (GDP)						
Mean	1.42	0.59	0.47	-2.64	-0.04	-4.06
t-stat	[0.93]	[0.30]	[0.31]	[-1.46]	[-0.03]	[-1.94]
C. Real money growth (M)						
Mean	2.74	0.36	-0.56	-3.06	-0.13	-5.80
t-stat	[1.44]	[0.20]	[-0.40]	[-2.29]	[-0.10]	[-3.10]
D. Real GDP growth + real money growth (MIUF)						
Mean	3.25	0.33	-0.15	-4.09	-0.17	-7.35
t-stat	[1.66]	[0.20]	[-0.11]	[-2.76]	[-0.12]	[-3.69]
E. Taylor rule fundamentals (TRF)						
Mean	0.32	1.47	-0.56	-0.66	0.14	-0.98
t-stat	[0.23]	[1.19]	[-0.45]	[-0.46]	[0.12]	[-0.83]
F. Real exchange rate (RER)						
Mean	-0.57	-0.76	-0.02	1.79	0.11	2.36
t-stat	[-0.35]	[-0.47]	[-0.01]	[1.56]	[0.09]	[1.75]

Table 4. Correlation Coefficients of High Minus Low Portfolios' Excess Returns

Correlation coefficients of high minus low portfolios' excess returns for the strategies based on the carry trade (CT), real GDP growth (RGDP), real money growth (RM), real GDP plus real money growth (MIUF), Taylor-rule fundamentals (TRF), real exchange rate with base year 1973 (RER). The sample period is 1974Q1–2010Q3.

	RGDP	RM	MIUF	TRF	RER
CT	0.20	-0.03	0.18	0.76	0.55
RGDP		0.53	0.83	0.41	0.41
RM			0.79	0.18	0.12
MIUF				0.41	0.42
TRF					0.67

Table 5. Descriptive statistics for FX Investment Strategies Based on Macro Fundamentals

Descriptive statistics for three zero-cost portfolios based on the carry trade (CT), real money growth plus real GDP growth (MIUF), real exchange rates (RER), and a combined strategy (equal weighted average of the three individual strategies). AC(1) denotes first-order return autocorrelation.

	Carry Trade	MIUF	RER	Combined
Mean	6.10	6.22	4.47	5.60
$t-stat$	3.78	3.39	2.82	5.38
Median	6.57	4.48	6.86	5.55
Standard Deviation	9.30	9.60	8.69	5.17
Sharpe Ratio	0.66	0.65	0.51	1.08
Skewness	-0.55	0.04	-0.53	-0.14
Kurtosis	3.89	3.08	3.20	3.06
AC(1)	0.08	0.17	0.08	0.21
$p-value$	0.61	0.12	0.62	0.04

Table 6. Decomposition of return predictability

This table reports results on the decomposition of the covariance between predictors and future excess returns into different components, a "static" trade, "dynamic" trade (Dyn), and a "dollar" trade (Dol), in the left panel ("Portfolio"). Combining the static and dynamic trade yields a cross-sectional currency portfolio ("CS") which exploits persistent differences in the cross-section of countries' fundamentals for forecasting and portfolio formation, whereas combining the dynamic and dollar trade yields a time-series portfolio ("TS") which exploits variation in countries' fundamentals over time for forecasting and portfolio formation. The decomposition is based on Hassan and Mano (2013) and explained in more detail in Section 5 to which we refer for details. The right panel ("Correlations") shows return correlations of these trading strategies with our portfolios reported in Table 1 above.

	Portfolio					Correlations				
	Static	Dyn	Dol	CS	TS	Static	Dyn	Dol	CS	TS
Interest rate differentials										
Mean	0.65	0.15	0.27	0.80	0.41	0.37	0.40	0.08	0.52	0.36
t	[3.29]	[0.73]	[1.56]	[2.83]	[1.48]					
SR	0.66	0.13	0.34	0.52	0.29					
Real GDP growth										
Mean	-0.46	0.17	0.27	-0.29	0.44	0.62	0.03	0.10	0.65	0.10
t	[-1.74]	[0.79]	[0.85]	[-0.99]	[1.18]					
SR	-0.29	0.14	0.19	-0.19	0.23					
Real money growth										
Mean	-0.79	-0.47	0.26	-1.26	-0.21	0.48	0.15	-0.10	0.59	0.02
t	[-1.74]	[-1.22]	[0.52]	[-2.40]	[-0.33]					
SR	-0.31	-0.22	0.10	-0.48	-0.06					
MIUF										
Mean	-1.25	-0.35	0.54	-1.59	0.19	0.67	-0.08	0.03	0.64	-0.03
t	[-1.76]	[-0.68]	[0.70]	[-2.12]	[0.21]					
SR	-0.31	-0.12	0.15	-0.41	0.04					
Real exchange rate										
Mean	6.03	1.21	1.73	7.24	2.94	0.57	0.43	0.12	0.65	0.25
t	[2.46]	[0.61]	[0.36]	[2.05]	[0.52]					
SR	0.39	0.11	0.07	0.34	0.10					

Table 7. Loadings on Business Cycle Variables

This Table reports factor loadings (betas) of FX portfolio excess returns on business cycle variables obtained via standard time-series OLS regressions. The portfolios are sorted according to interest rate differentials (CT), real money and GDP growth (MIUF) and real-exchange rates (RER), i.e. there are 12 portfolios included. The business cycle variables include the quarterly growth rate of industrial production IP(q), annual growth rate of industrial production IP(a), quarterly growth rate of GDP, annual growth rate of GDP, quarterly growth rate of non-durables and services consumption (NDS) and durables consumption (DUR). All regressions also include a constant as well as the DOL factor by Lustig, Roussanov, and Verdelhan (2011) (coefficients not reported); the business cycle variables have been standardized. HAC robust t-statistics (with Newey-West adjustment of 4 lags) are reported in parentheses. Also p-values from testing the following restrictions via Wald tests are reported: W1 tests if the loadings of the two extreme portfolios are the same ($\beta_H = \beta_L$) for each of the three set of test assets, W2 tests the joint significance of all loadings. The data are quarterly and span the period: 1974Q1–2010Q3.

	CT				**MIUF**				**RER**				**Joint Hyp. Tests**	
	Low	2	3	High	Low	2	3	High	Low	2	3	High	*p*-val. W1	*p*-val. W2
IP(q)	-0.31	-0.01	-0.10	0.39	0.01	-0.16	-0.03	0.32	-0.16	-0.05	-0.20	0.37	[0.11]	[0.01]
	(0.16)	(0.12)	(0.17)	(0.26)	(0.23)	(0.15)	(0.19)	(0.18)	(0.17)	(0.16)	(0.11)	(0.22)		
IP(a)	-0.24	-0.12	-0.07	0.39	-0.38	-0.15	0.23	0.33	-0.24	0.00	-0.11	0.33	[0.01]	[0.08]
	(0.17)	(0.16)	(0.15)	(0.30)	(0.24)	(0.14)	(0.19)	(0.17)	(0.15)	(0.17)	(0.15)	(0.25)		
GDP(q)	-0.28	-0.20	-0.26	0.71	0.19	-0.24	-0.13	0.29	-0.28	-0.17	-0.17	0.40	[0.04]	[0.01]
	(0.15)	(0.12)	(0.18)	(0.27)	(0.19)	(0.13)	(0.19)	(0.17)	(0.18)	(0.16)	(0.12)	(0.21)		
GDP(a)	-0.22	-0.23	-0.20	0.60	-0.33	-0.12	0.14	0.33	-0.23	-0.06	-0.19	0.37	[0.01]	[0.02]
	(0.15)	(0.14)	(0.14)	(0.28)	(0.21)	(0.14)	(0.19)	(0.17)	(0.15)	(0.17)	(0.14)	(0.26)		
NDS	-0.05	-0.20	-0.04	0.29	-0.20	-0.14	0.05	0.35	-0.10	0.11	-0.09	0.10	[0.24]	[0.39]
	(0.17)	(0.14)	(0.18)	(0.26)	(0.21)	(0.14)	(0.18)	(0.18)	(0.14)	(0.14)	(0.13)	(0.21)		
DUR	-0.19	-0.25	0.01	0.44	0.02	-0.11	-0.12	0.21	-0.04	-0.10	-0.12	0.02	[0.23]	[0.63]
	(0.16)	(0.15)	(0.13)	(0.25)	(0.24)	(0.14)	(0.16)	(0.18)	(0.15)	(0.15)	(0.15)	(0.22)		

Table 8. Asset Pricing Tests with Business Cycle Factors

This Table presents results of asset pricing tests with business cycle. The test assets are 3 pooled sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money and GDP growth (MIUF), and real-exchange rates (RER), i.e. there are 12 portfolios in total. The business cycle variables include the quarterly growth rate of industrial production IP(q), annual growth rate of industrial production IP(a), quarterly growth rate of GDP, and the annual growth rate of GDP. Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [·] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

	IP(q)	IP(a)	GDP(q)	GDP(a)	HJ-Dist.	R^2
(i)	3.07				0.53	0.69
	(1.77)				[0.00]	
(ii)		8.75			0.43	0.79
		(3.22)			[0.30]	
(iii)			1.00		0.52	0.56
			(2.03)		[0.01]	
(iv)				3.61	0.47	0.76
				(2.23)	[0.12]	

Table 9. Asset Pricing Tests: Consumption-based Factors

This Table presents results of asset pricing tests with consumption-based risk factors. The test assets are 3 pooled sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money and GDP growth (MIUF), and real-exchange rates (RER), i.e. there are 12 portfolios in total. Panel A reports results for unconditional models with non-durables and services (NDS) consumption growth Δc_{t+1} and durables consumption growth (DUR) Δdc_{t+1}. Panel B reports results of conditional specifications of the CCAPM with scaled factors. B.1 uses Lettau and Ludvigson's (2001) consumption-wealth ratio *cay* as a conditioning variable, and B.2 uses a measure of the output gap. Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [·] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

Panel A:	**Unconditional Models**						
		Δc_{t+1}			Δdc_{t+1}	HJ-Dist.	R^2
	(i)	1.00				0.52	0.59
		(1.99)				[0.03]	
	(ii)	0.90			0.76	0.52	0.62
		(1.54)			(1.38)	[0.02]	
Panel B:	**Conditional Models**						
B.1 cay		Δc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t		HJ-Dist.	R^2
	(iii)	0.48	1.17	1.99		0.34	0.95
		(1.39)	(2.99)	(1.50)		[0.65]	
	(iv)	0.45	1.11			0.34	0.94
		(1.53)	(2.96)			[0.55]	
	(v)		1.17			0.37	0.92
			(4.96)			[0.20]	
	(vi)			2.99		0.41	0.85
				(3.84)		[0.42]	
B.2 gap		Δc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t		HJ-Dist.	R^2
	(vii)	0.19	1.07	0.13		0.31	0.92
		(0.69)	(2.18)	(0.12)		[0.72]	
	(viii)	0.16	1.29			0.42	0.88
		(0.70)	(3.15)			[0.24]	
	(ix)		1.53			0.44	0.88
			(4.40)			[0.12]	
	(x)			2.17		0.40	0.84
				(4.67)		[0.51]	

Internet Appendix

Currency Risk Premia and Macro Fundamentals

(Not for Publication)

Table A.1. Portfolio Sorts: Alternative Value Measures

Portfolio mean excess returns from P1 (low values) to P4 (high values) based on the country characteristics indicated in the heading of each table section. "Av." denotes the average of all four portfolios and "P4-P1" is a high minus low portfolio. NW t-stats in brackets. The sample period is 1974Q1 – 2010Q3.

	P1	P2	P3	P4	Av.	P4-P1
A. Real exchange rate (base year 2009)						
Mean	-2.37	0.23	0.56	3.79	0.55	6.16
t-stat	[-1.71]	[0.17]	[0.29]	[2.31]	[0.42]	[3.67]
B. Real exchange rate (deviation from 5-year average)						
Mean	-1.38	0.84	0.31	2.45	0.56	3.83
t-stat	[-0.98]	[0.47]	[0.21]	[1.59]	[0.43]	[2.40]
C. Exchange rate changes (5 years)						
Mean	-0.83	-0.05	-0.28	3.41	0.56	4.25
t-stat	[-0.56]	[-0.03]	[-0.20]	[1.83]	[0.43]	[2.39]

Table A.2. Rank portfolios

This table shows results for rank portfolios where we always use all currencies to construct a long-short portfolio. To do so, we compute the ranking of each currency according to some signal (e.g., interest rate differentials) at the end of each year and the portfolio weight of a currency is then given by the rank of a currency minus the average rank across currencies. The weights of all currencies are then multiplied by a constant c which rescales the portfolio weights such that (i) the absolute portfolio weights sum to two in absolute value (one dollar long, one dollar short), or (ii) that the ex-ante expected portfolio volatility is equal to 10% p.a. We use rolling windows over the last 5 years to compute historical volatilities for all currencies and then use these historical volatilities as forecasts for future volatilities to come up with an ex ante expected portfolio volatility. We report average excess returns (left part) and spot exchange rate changes (right part, "FX return") for both rescaling methods and for three different signals: (Lagged) interest rate differentials (CT), real money plus GDP growth (MIUF), and the real exchange rate (RER). In addition, we report results for the full portfolio and two sub-portfolios based only on the positive and negative portfolio weights, respectively. t denotes a t-statistics for the test of a zero portfolio return, and SR denotes the annualized Sharpe Ratio.

	Excess returns			FX return		
	CT	MIUF	RER	CT	MIUF	RER
	Panel A. One dollar long, one dollar short					
	Total portfolio					
Mean	5.71	-5.19	4.83	2.69	-2.30	0.88
t	[3.93]	[-3.58]	[3.23]	[1.64]	[-1.27]	[0.48]
SR	0.71	-0.68	0.57	0.30	-0.27	0.09
	Only positive weights					
Mean	3.91	-1.44	3.22	0.90	-1.64	-0.78
t	[2.29]	[-1.11]	[2.18]	[0.46]	[-1.25]	[-0.42]
SR	0.44	-0.22	0.45	0.09	-0.25	-0.09
	Only negative weights					
Mean	1.80	-3.75	1.62	1.80	-0.66	1.66
t	[1.32]	[-2.21]	[1.09]	[1.32]	[-0.32]	[1.11]
SR	0.26	-0.43	0.19	0.26	-0.07	0.20
	Panel B.Constant volatility					
	Total portfolio					
Mean	3.89	-4.11	3.68	2.26	-2.08	1.90
t	[1.99]	[-2.09]	[2.00]	[1.31]	[-1.25]	[1.14]
SR	0.34	-0.39	0.32	0.22	-0.23	0.18
	Only positive weights					
Mean	1.81	-2.40	0.31	0.52	-1.77	-0.71
t	[0.61]	[-1.15]	[0.12]	[0.20]	[-0.88]	[-0.32]
SR	0.12	-0.24	0.03	0.04	-0.19	-0.07
	Only negative weights					
Mean	2.07	-1.71	3.38	1.74	-0.31	2.61
t	[0.82]	[-0.57]	[1.11]	[0.81]	[-0.12]	[0.92]
SR	0.16	-0.11	0.21	0.17	-0.02	0.19

Table A.3. Portfolio Sorts: Skipping One Quarter Before Portfolio Formation

This table is similar to Table 1 but here we sort on macro variables which are lagged an additional quarter to account for the fact that we are not using real-time data.

	P1	P2	P3	P4	Av.	P4-P1
A. Carry Trade						
Mean	-2.04	0.19	0.53	3.47	0.54	5.51
t-stat	[-1.45]	[0.14]	[0.36]	[1.92]	[0.42]	[3.39]
B. Real GDP growth						
Mean	2.19	0.36	1.43	-1.80	0.54	-3.99
t-stat	[1.38]	[0.22]	[0.99]	[-1.20]	[0.42]	[-2.29]
C. Real money growth						
Mean	3.83	0.35	-0.93	-1.24	0.50	-5.07
t-stat	[2.13]	[0.23]	[-0.71]	[-0.94]	[0.39]	[-3.17]
D. Real GDP growth + real money growth						
Mean	3.65	-0.06	0.58	-2.28	0.47	-5.93
t-stat	[2.11]	[-0.04]	[0.39]	[-1.64]	[0.36]	[-3.46]
E. Taylor rule fundamentals						
Mean	-0.50	1.10	0.06	2.07	0.68	2.57
t-stat	[-0.36]	[0.93]	[0.05]	[1.33]	[0.60]	[1.68]
F. Real exchange rate (base year 1973)						
Mean	-1.26	-0.39	1.32	3.08	0.69	4.34
t-stat	[-0.98]	[-0.27]	[1.05]	[2.08]	[0.60]	[2.82]

Table A.4. Asset Pricing with Business Cycle Factors: Individual Cross-Sections

This Table presents results of asset pricing tests with business cycle and term structure factors. The test assets are 3 individual sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money and GDP growth (MIUF), and real-exchange rates (RER). The business cycle variables include the quarterly growth rate of industrial production IP(q), annual growth rate of industrial production IP(a), quarterly growth rate of GDP, and annual growth rate of GDP. The term structure factors include the relative T-Bill rate (RTB), short rate innovations (UTB) and term spread innovations (UT). Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [·] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

Panel A: CT	IP(q)	IP(a)	GDP(q)	GDP(a)	HJ-Dist.	R^2
(i)	3.36				0.12	0.97
	(1.42)				[0.80]	
(ii)		10.58			0.10	0.96
		(1.69)			[0.88]	
(iii)			0.99		0.22	0.85
			(1.92)		[0.29]	
(iv)				3.23	0.23	0.83
				(1.76)	[0.19]	
Panel B: MIUF	IP(q)	IP(a)	GDP(q)	GDP(a)	HJ-Dist.	R^2
(i)	3.75				0.22	0.62
	(1.83)				[0.49]	
(ii)		7.57			0.24	0.74
		(1.63)			[0.12]	
(iii)			0.71		0.30	0.25
			(1.63)		[0.07]	
(iv)				4.55	0.19	0.85
				(2.11)	[0.49]	
Panel C: RER	IP(q)	IP(a)	GDP(q)	GDP(a)	HJ-Dist.	R^2
(i)	2.40				0.30	0.47
	(1.40)				[0.08]	
(ii)		8.85			0.26	0.66
		(1.61)			[0.35]	
(iii)			1.30		0.24	0.72
			(1.66)		[0.40]	
(iv)				3.56	0.29	0.56
				(1.24)	[0.13]	

Table A.5. Consumption-based Asset Pricing Models: Individual Cross-Sections

This Table presents results of asset pricing tests with consumption-based risk factors. The test assets are 3 individual sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money and GDP growth (MIUF), and real-exchange rates (RER). Panel A reports results for unconditional models with non-durables and services (NDS) consumption growth Δc_{t+1} and durables consumption growth (DUR) Δdc_{t+1}. Panel B reports results of conditional specifications of the CCAPM with scaled factors. B.1 uses a measure of the consumption surplus ratio in the spirit of habit models as the conditioning variable, B.2 uses Lettau and Ludvigson's (2001) consumption-wealth ratio *cay* as a conditioning variable, and B.3 uses a measure of the output gap. Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [·] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

Panel A: CT		Δc_{t+1}	Δdc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t	**HJ-Dist.**	R^2
Unconditional Model	(i)	1.03				0.31	0.64
		(1.19)				[0.11]	
	(ii)	-0.71	1.23			0.15	0.93
		(-0.27)	(1.01)			[0.63]	
Conditional Model	(iii)			1.60		0.13	0.96
$z_t = cay_t$				(1.61)		[0.84]	
	(iv)				3.11	0.19	0.79
					(2.29)	[0.27]	
Conditional Model	(v)			2.20		0.18	0.93
$z_t = gap_t$				(1.59)		[0.68]	
	(vi)				2.87	0.24	0.86
					(1.68)	[0.30]	
Panel B: MIUF		Δc_{t+1}	Δdc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t	HJ-Dist.	R^2
Unconditional Model	(i)	1.06				0.14	0.92
		(1.77)				[0.76]	
	(ii)	1.07	0.62			0.14	0.92
		(1.62)	(0.77)			[0.53]	
Conditional Model	(iii)			2.15		0.09	0.97
$z_t = cay_t$				(1.35)		[0.93]	
	(iv)				4.02	0.14	0.94
					(1.35)	[0.78]	
Conditional Model	(v)			1.43		0.31	0.76
$z_t = gap_t$				(2.76)		[0.08]	
	(vi)				1.86	0.24	0.81
					(2.24)	[0.24]	
Panel C: RER		Δc_{t+1}	Δdc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t	HJ-Dist.	R^2
Unconditional Model	(i)	0.68				0.32	0.05
		(0.94)				[0.00]	
	(ii)	0.84	0.87			0.31	0.06
		(0.76)	(0.58)			[0.15]	
Conditional Model	(iii)			0.97		0.23	0.76
$z_t = cay_t$				(4.09)		[0.11]	
	(iv)				3.24	0.28	0.61
					(2.09)	[0.04]	
Conditional Model	(v)			1.71		0.27	0.77
$z_t = gap_t$				(1.84)		[0.07]	
	(vi)				4.01	0.17	0.89
					(1.02)	[0.83]	

Table A.6. Asset Pricing with Business Cycle Factors: Expanded Cross-Section

This Table presents results of asset pricing tests with business cycle and term structure factors. The test assets are 6 pooled sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money growth, real GDP growth, real money and GDP growth (MIUF), and real-exchange rates (RER) based on two different base years, i.e. there are 24 portfolios in total. The business cycle variables include the quarterly growth rate of industrial production IP(q), annual growth rate of industrial production IP(a), quarterly growth rate of GDP, and annual growth rate of GDP. The term structure factors include the relative T-Bill rate (RTB), short rate innovations (UTB) and term spread innovations (UT). Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [·] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

	IP(q)	IP(a)	GDP(q)	GDP(a)	HJ-Dist.	R^2
(i)	2.16				0.64	0.54
	(2.17)				[0.00]	
(ii)		5.79			0.64	0.67
		(2.84)			[0.01]	
(iii)			0.80		0.64	0.42
			(2.28)		[0.00]	
(iv)				2.89	0.64	0.71
				(2.65)	[0.01]	

Table A.7. Consumption-based Asset Pricing Models: Expanded Cross-Section

This Table presents results of asset pricing tests with consumption-based risk factors. The test assets are 6 pooled sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT), real money growth, real GDP growth (GDP), real money (M) and GDP growth (MIUF), and real-exchange rates (RER and RER2) based on two different base years, i.e. there are 24 portfolios in total. Panel A reports results for unconditional models with non-durables and services (NDS) consumption growth Δc_{t+1} and durables consumption growth (DUR) Δdc_{t+1}. Panel B reports results of conditional specifications of the CCAPM with scaled factors. B.1 uses a measure of the consumption surplus ratio in the spirit of habit models as the conditioning variable, B.2 uses Lettau and Ludvigson's (2001) consumption-wealth ratio *cay* as a conditioning variable, and B.3 uses a measure of the output gap. Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. t-statistics for the factor risk prices are reported in parentheses and are based on the Newey and West (1987) correction with optimal lag length selection by Andrews (1991) and also account for estimation of factor means and the factor covariance matrix. The Hansen and Jagannathan (1997) distance (HJ-dist.) is also reported together with the simulation-based p-value [$\cdot$] of the test whether the HJ-distance is equal to zero. The data are quarterly and span the period: 1974Q1–2010Q3.

Panel A:	**Unconditional Models**						
		Δc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t	Δdc_{t+1}	**HJ-Dist.**	R^2
	(i)	0.67				0.64	0.48
		(2.60)				[0.00]	
	(ii)	0.62			0.53	0.64	0.50
		(1.73)			(1.93)	[0.01]	
Panel B:	**Conditional Models**						
B.1	*Consumption-Wealth Ratio cay*						
		Δc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t		HJ-Dist.	R^2
	(iii)	0.38	0.87	0.71		0.48	0.92
		(2.25)	(5.59)	(0.99)		[0.06]	
	(iv)	0.39	0.88			0.56	0.92
		(2.25)	(5.22)			[0.02]	
	(v)		0.98			0.57	0.88
			(9.44)			[0.01]	
	(vi)			2.30		0.64	0.82
				(4.68)		[0.01]	
B.2	*Output Gap*						
		Δc_{t+1}	$z_t \cdot \Delta c_{t+1}$	z_t		HJ-Dist.	R^2
	(vii)	0.10	1.10	0.47		0.47	0.91
		(0.73)	(4.02)	(0.77)		[0.30]	
	(viii)	0.11	1.11			0.57	0.89
		(0.80)	(4.19)			[0.06]	
	(ix)		1.29			0.57	0.89
			(5.43)			[0.04]	
	(x)			1.70		0.64	0.84
				(4.42)		[0.00]	

Table A.8. Asset Pricing with Business Cycle and CRR Factors

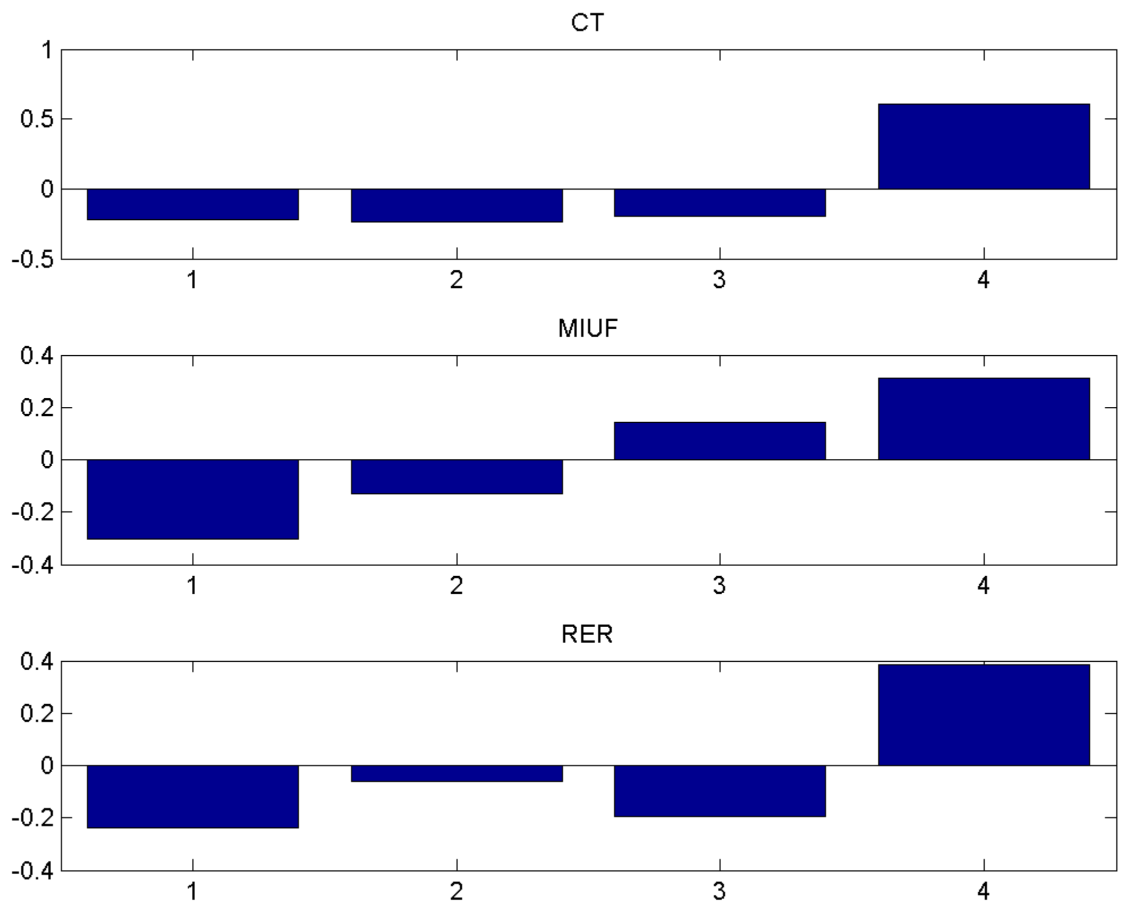
This Table presents results of asset pricing tests with IP growth and term structure factors (Panel A) and other Chen/Roll/Ross factors (Panel B). The test assets are 3 groups of FX portfolios that are pooled together: Portfolios 11 to 14 are sorted according to interest rate differentials (CT), portfolios 21-24 are sorted by real money and GDP growth (MIUF), and portfolios 31 to 34 are based on sorts by real-exchange rates (RER), i.e. there are 12 portfolios included. The business cycle variables include the quarterly growth rate of industrial production IP(q), annual growth rate of industrial production IP(a), quarterly growth rate of GDP, annual growth rate of GDP, quarterly growth rate of non-durables and services consumption (NDS) and durables consumption (DUR). The term structure factors include the relative T-Bill rate (RTB), short rate innovations (UTB) and term spread innovations (UT). The CRR factors include expected inflation (EINF), and unexpected inflation (UINF) obtained from fitting an AR(1) to monthly U.S. CPI inflation. Additionally the term spread (TS) and the default spread (DF) are considered. Results are based on GMM estimation of corresponding specification of the SDF. The table reports implied factor risk premia $\widehat{\lambda}$; SDF parameters and coefficients on the DOL factor are omitted to conserve space. HAC robust standard errors are based on the Newey-West correction with optimal lag length selection by Andrews (1993) and also account for estimation of factor means and the factor covariance matrix. The data are quarterly and span the period: 1974Q1 – 2010Q3.

Panel A:	**IP Growth and Term-Structure Factors**							
	IP(q)	IP(a)	RTB	UTB	UTS		HJ-Dist.	R^2
(i)			1.32				0.43	0.60
			(1.82)				[0.49]	
(ii)	2.79		1.19				0.43	0.69
	(1.96)		(1.39)				[0.40]	
(iii)		7.31	1.24				0.41	0.78
		(1.93)	(1.74)				[0.33]	
(iv)				1.11			0.45	0.59
				(1.62)			[0.34]	
(v)	1.88			0.81			0.45	0.66
	(2.01)			(1.07)			[0.26]	
(vi)		6.11		0.76			0.40	0.79
		(2.04)		(1.02)			[0.32]	
(vii)					-1.46		0.45	0.69
					(-1.38)		[0.33]	
(viii)	1.49				-1.07		0.44	0.75
	(1.63)				(-1.37)		[0.33]	
(ix)		5.72			-0.99		0.38	0.85
		(2.38)			(-1.27)		[0.45]	
Panel B:	**IP Growth and Chen/Roll/Ross Factors**							
	IP(q)	IP(a)	EINF	UNINF	TS	DF	HJ-Dist.	R^2
(i)			0.85				0.51	0.36
			(2.05)				[0.06]	
(ii)	1.88		0.42				0.49	0.73
	(1.46)		(0.88)				[0.03]	
(iii)		8.25	-0.09				0.42	0.74
		(1.79)	(-0.10)				[0.33]	
(iv)				0.68			0.51	0.47
				(1.35)			[0.06]	
(v)	2.28			0.24			0.50	0.64
	(1.62)			(0.49)			[0.04]	
(vi)		8.30		0.00			0.42	0.74
		(2.62)		(0.01)			[0.46]	
(vii)					-1.55		0.50	0.28
					(-2.16)		[0.07]	
(viii)	2.75				-0.97		0.49	0.74
	(1.46)				(-0.91)		[0.05]	
(ix)		8.54			-0.41		0.43	0.76
		(2.78)			(-0.34)		[0.27]	
(x)						-0.82	0.54	0.33
						(-0.98)	[0.00]	
(xi)	3.00					-0.55	0.52	0.70
	(1.60)					(-0.77)	[0.00]	
(xii)		8.60				-0.58	0.42	0.76
		(2.62)				(-1.22)	[0.30]	

Table A.9. Asset Pricing Tests: Monte Carlo Results

Panel A: N=4	T=100	T=150	T=200	T=500	T=1,000	T=5,000	T=10,000
Median b_1	0.035	0.036	0.038	0.042	0.043	0.044	0.044
Median b_2	2.314	2.921	3.358	4.512	4.921	5.164	5.187
Bias b_1	-0.212	-0.184	-0.145	-0.053	-0.035	-0.003	-0.003
Bias b_2	-0.557	-0.441	-0.358	-0.137	-0.058	-0.012	-0.007
Freq. b_1 sign. at 5%	0.338	0.480	0.606	0.919	0.991	1.000	1.000
Freq. b_2 sign. at 5%	0.118	0.217	0.328	0.786	0.970	1.000	1.000
Median λ_1	0.331	0.331	0.334	0.334	0.332	0.330	0.329
Median λ_2	0.432	0.546	0.630	0.845	0.926	0.975	0.980
Bias λ_1	0.006	0.005	0.013	0.013	0.008	0.001	-0.001
Bias λ_2	-0.561	-0.446	-0.361	-0.143	-0.061	-0.011	-0.006
Freq. λ_1 sign. at 5%	0.335	0.476	0.604	0.919	0.991	1.000	1.000
Freq. λ_2 sign. at 5%	0.117	0.216	0.325	0.785	0.970	1.000	1.000
Median R^2	0.643	0.736	0.787	0.911	0.955	0.991	0.995
Freq. J_T sign. at 5%	0.112	0.126	0.120	0.090	0.061	0.049	0.051
Panel B: N=12	**T=100**	**T=150**	**T=200**	**T=500**	**T=1,000**	**T=5,000**	**T=10,000**
Median b_1	0.038	0.038	0.040	0.042	0.043	0.044	0.044
Median b_2	2.190	2.703	3.084	4.131	4.612	5.097	5.165
Bias b_1	-0.144	-0.145	-0.097	-0.054	-0.032	-0.010	-0.006
Bias b_2	-0.581	-0.483	-0.410	-0.210	-0.117	-0.025	-0.012
Freq. b_1 sign. at 5%	0.781	0.908	0.964	1.000	1.000	1.000	1.000
Freq. b_2 sign. at 5%	0.622	0.819	0.925	0.999	1.000	1.000	1.000
Median λ_1	0.366	0.350	0.350	0.340	0.335	0.331	0.330
Median λ_2	0.406	0.505	0.579	0.776	0.870	0.961	0.974
Bias λ_1	0.109	0.061	0.061	0.031	0.016	0.005	0.001
Bias λ_2	-0.588	-0.488	-0.412	-0.213	-0.117	-0.025	-0.012
Freq. λ_1 sign. at 5%	0.778	0.908	0.964	1.000	1.000	1.000	1.000
Freq. λ_2 sign. at 5%	0.621	0.817	0.924	0.999	1.000	1.000	1.000
Median R^2	0.459	0.548	0.626	0.808	0.895	0.977	0.988
Freq. J_T sign. at 5%	0.590	0.511	0.444	0.250	0.156	0.073	0.058

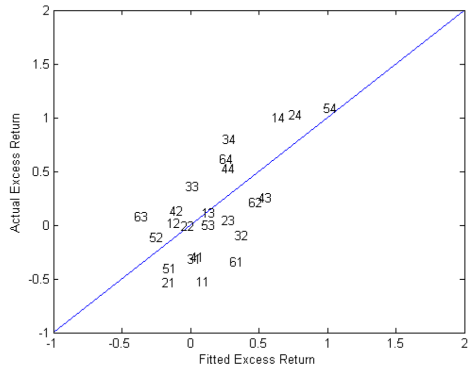
Figure A.1. Business Cycle Sensitivity of FX Portfolios



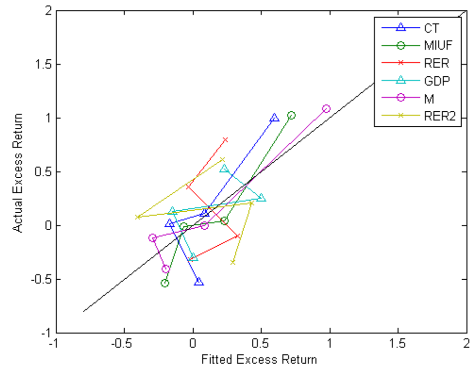
(a) GDP Growth (YoY)

The Figure shows loadings of FX portfolio returns on the annual growth rate of GDP, obtained via time-series regressions. The test assets are 3 groups of FX portfolios that are pooled together in the tests: Portfolios 11 to 14 are sorted according to interest rate differentials (CT), portfolios 21-24 are sorted by real money and GDP growth (MIUF), and portfolios 31 to 34 are based on sorts by real-exchange rates (RER), i.e. there are 12 portfolios included. The data are quarterly and span the period: 1974Q1–2010Q3.

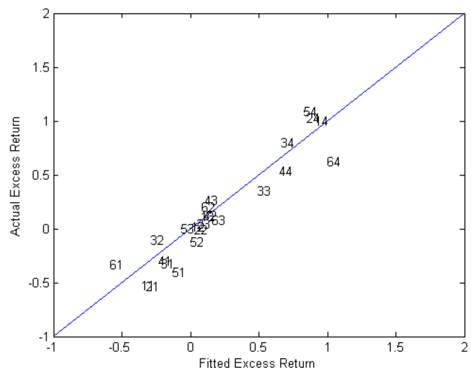
Figure A.2. Pricing Error Plots: Expanded Cross-Section



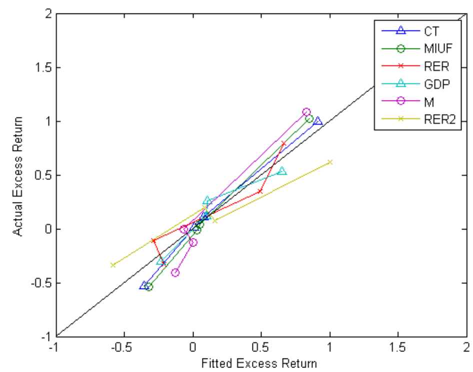
(a) Δc_{t+1}



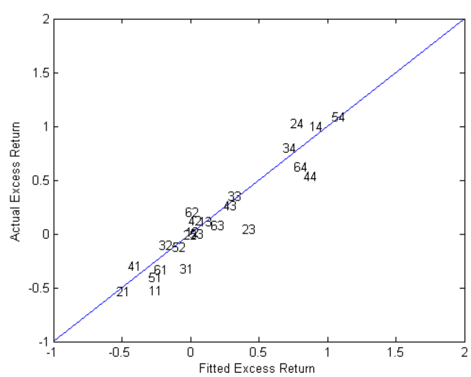
(b) Δc_{t+1}



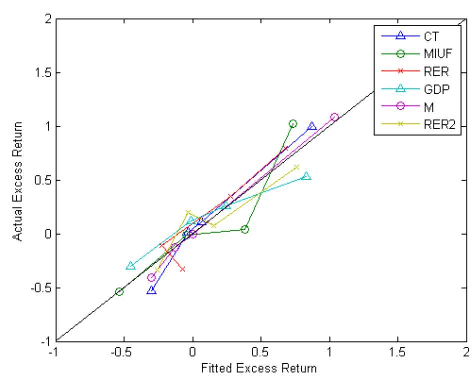
(c) $cay_t \cdot \Delta c_{t+1}$



(d) $cay_t \cdot \Delta c_{t+1}$



(e) $gap_t \cdot \Delta c_{t+1}$



(f) $gap_t \cdot \Delta c_{t+1}$

The Figure shows selected pricing error plots for unconditional and scaled versions of consumption-based asset pricing models.The test assets are 6 pooled sets of FX portfolios: 4 portfolios for each set, sorted on interest rate differentials (CT, 11-14), real money and GDP growth (MIUF, 21-24), real-exchange rates with base year 1973 (RER, 31-34), real GDP growth (GDP, 41-44), real money growth (M, 51-54), and real-exchange rates with base year 2009 (RER2, 61-64), i.e. there are 24 portfolios in total. The graphs are based on GMM estimation of corresponding specification of a two-factor SDF which includes the DOL factor and the indicated factor. The right hand graphs show plots where, for each group, the solid lines connect portfolios from low to high values of the sorting characteristic. The data are quarterly and span the period: 1974Q1-2010Q3.