Safe Haven Currencies: A Portfolio Perspective*

Gino Cenedese†

Bank of England

This draft: December 2012

Abstract

Market participants often say that investors move into "safe haven" currencies in periods of market stress. What defines these safe haven currencies? In this paper, I ask specifically: what currencies provide hedging benefits in times of stress by becoming less correlated with risky assets such as US equities? I find that the foreign exchange market exhibits asymmetric correlations: during periods of bear, volatile world equity markets, currencies provide different hedging benefits than in bull markets. I show how these time-varying hedging benefits depend on currency characteristics. This helps to identify what fundamentals make a currency a safe haven in times of market stress. This paper also illustrates how the presence of regime shifts in financial markets affects optimal portfolio choice across currencies: during bear markets, investors are better off by unwinding carry trade positions, and by following currency momentum. Also, diversification benefits are increased by holding undervalued currencies and currencies of countries with strong current accounts and international investment positions.

Keywords: Foreign Exchange, Safe Haven Currencies, Portfolio Choice, Uncovered Interest Rate Parity, Carry Trade, Purchasing Power Parity, Markov-switching.
JEL Classification: F31, G11, G15.

* **Acknowledgments:** I am grateful for useful conversations and constructive comments to David Barr, Monica Billio, Martin Brooke, Pasquale Della Corte, Maurizio Habib, Bob Hills, John Hooley, Daniele Massacci, Thomas Nitschka, Lucio Sarno, and participants at the Centre for Central Banking Studies of the Bank of England, and the 2nd ECB/BdI Workshop on Financial Determinants of Exchange Rates. Discussions with Filip Žikeš were particularly helpful. All the remaining errors are my own. The views expressed in this paper are those of the author, and not necessarily those of the Bank of England.

†International Finance Division, Bank of England, Threadneedle Street, London EC2R 8AH. E-mail: gino.cenedese@bankofengland.co.uk.

1 Introduction

In times of market stress, market participants tend to rebalance their portfolios toward “safe” assets. In particular, the financial press usually suggests that these safe haven assets are usually denominated in US dollars and a small group of other currencies. But why are these currencies perceived as safe? More specifically, what common characteristics make some currencies a safe haven asset? And are currency characteristics and safe haven behaviour related unconditionally, or does their link become stronger only in periods of heightened market stress?

There is surprisingly little empirical work on the study of safe haven currencies, which appears even more striking when compared to the wide coverage of this issue in the financial press. Ranaldo and Söderlind (2010) define a safe haven asset as an asset that either provides hedging benefits on average or in times of stress. They find that the Swiss franc, the Japanese yen, and the British pound display safe haven behaviour. A limitation of their study, as they acknowledge, is that they focus on short-run returns, with little to say on the potential influence of macroeconomic fundamentals on longer-run exchange rate movements. Habib and Stracca (2012) go a step further and try to identify the fundamentals of safe haven currencies, defined as those currencies that provide a hedge for a reference portfolio of risky assets. Using panel regressions, they find that only a few factors are robustly associated to a safe haven status, most notably the net foreign asset position. However, their framework does not allow for the presence of asymmetric behaviour of the currencies in bear versus bull markets.

This paper investigates how the presence of regime shifts in financial markets, characterised by “tranquil” and “crisis” states, can affect the asset allocation of international investors among different currencies. I do this in three steps. First, I start by building currency portfolios, which focuses attention on currency characteristics, and away from the idiosyncrasies of individual exchange rates. Another reason to study portfolios, as highlighted by Cochrane (2005), is that individual assets have high volatilities, so it is difficult to accurately measure their expected return, betas, and covariances. Instead, portfolios have lower volatilities by diversification. Forming portfolios also avoids having to model individual expected returns or covariances that vary over time as the characteristics vary. Second, I analyse how a model inspired by the world CAPM with regime switching can capture the asymmetric correlations between the currency portfolios and the world equity market in different states of the world. This is a key feature of the model in that it allows to gauge the time-varying hedging benefits of the different currency portfolios. To some extent, the model can therefore analyse the safe haven properties of an asset. Indeed, an asset can be considered a safe haven if it is a "rainy-day" asset, i.e., an asset that performs well when the reference portfolio suffers losses, so that its hedging benefits increase in times of stress. Finally, I study the optimal allocation of an international investor that recognizes the presence of different regimes.

This paper finds that the foreign exchange market exhibits asymmetric correlations: during periods of bear, volatile world equity markets, currency portfolios provide different hedging benefits than in bull markets. The model can generate correlations between the currency portfolios and the world equity market that are higher in bear markets. I show how these time-varying hedging benefits depend on currency characteristics. For example, high-interest rate currencies have, in the bear market regime, a correlation with the world market that is about four times larger than in the normal market regime. In contrast, the correlations of low-interest rate currencies with the world market barely change and, if anything, they slightly decrease during bear markets. Analogous behaviour can be seen when focusing on other characteristics. With the estimates of the econometric model at hand, I show how the time-varying opportunity set translates into the optimal asset allocation of investors' wealth. In most cases, the optimal allocation in the tranquil regime is close to a balanced, equally weighted strategy. In contrast, the high-volatility, bear market regime is characterised by a significant shift in the optimal allocations. For example, an investor is best off by allocating more than 50 per cent of her wealth to low-interest-rate currencies, and going short high-interest-rate currencies. An analogous result holds for portfolios of currencies sorted by the net international investment position (IIP) of the country where the currency is legal tender. Also, during market stress, an investor would hold currencies of countries with stronger current accounts, and short currencies of countries with weaker current accounts. Taken together, these two latter results suggest that external sustainability seem to matter in analysing safe-haven behaviour of currencies, regardless of whether one takes a flow or stock perspective.

This paper is also related to the recent literature on the foreign exchange market that aims to explain the cross section of average exchange-rate returns by sorting currencies into portfolios according to their characteristics, in the same way that Fama and French (1992, 1993) sort stocks on size and book-to-market ratios to shift the focus from individual names to small/value versus large/growth stocks. Lustig and Verdelhan (2007) are the first to use this approach to explain why currencies with high-interest rates relative to the US dollar tend to appreciate rather than depreciate as implied by uncovered interest parity (UIP). Lustig et al. (2011) identify a slope factor that is similar to the Fama and French (1993) high-minus-low factor and that explains the cross section of expected returns of the interest-rate sorted portfolios. Menkhoff et al. (2012a) find that low interest rate currencies provide a hedge by yielding positive returns in times of unexpectedly high volatility. Della Corte et al. (2012) propose a global imbalance risk factor by sorting currencies by their countries' net international investment position (IIP). In another cross-sectional study, Menkhoff et al. (2012b) study currencies sorted by past cumulative returns (momentum) and find that their behaviour displays very different properties from those of interest-rate-sorted portfolios. Rafferty (2011) studies the behaviour of portfolios of currencies sorted by the deviation of their price from what implied by purchasing power parity (PPP). As these papers show, sorting currency by these characteristics tend to generate a large spread in the cross section of average returns. I select the currency characteristics to be analysed following the above literature. In addition, I also use the current account as a currency characteristic, to see if a flow perspective of external sustainability (as opposed to a stock perspective when using IIPs) matters as well, similarly to Habib and Stracca (2012).[1]

It should be noted that, though related, this paper does not attempt to identify the optimal hedging of the currency exposure of an internationally diversified equity or bond portfolio as in, e.g., Glen and Jorion (1993) and Campbell et al. (2010). Instead, this paper focuses on the optimal allocation of the portfolios of currencies in different regimes. I use the equity market as a benchmark asset used for evaluating the hedging properties of these portfolios. In this respect, my paper is closer to Kroencke et al. (2011), who look at the diversification benefits of popular foreign exchange investment styles such as the carry trade, momentum and value strategies. However, they do not consider presence of regime shifts in international markets and the relevant optimal allocation problem, which is key for understanding the safe haven behaviour of currencies. Barroso and Santa-Clara (2012) also study optimal currency portfolios and their diversification benefits for investors holding stocks and bonds. However, their parametric portfolios approach is very different from mine and does not allow for the presence of regime shifts, which is central to the present study.

Methodologically, this paper builds on the framework developed by Ang and Bekaert (2002). They are the first to analyse which portfolios should be held in different regimes for a small number of international equity markets, and find that the cost of ignoring such regimes can be very large. In particular, my paper is more closely related to Ang and Bekaert (2004), who use a regime switching specification in a world zero-beta CAPM for international equity markets. However, my application

[1] Barroso and Santa-Clara (2012) also analyse optimal currency portfolios using, among other fundamentals, the current account as a signal for portfolio formation. However, their parametric portfolio approach is different from previous studies as they do not sort currencies by their characteristics.

in the context of the foreign exchange market is novel in the literature. The contribution of this paper is therefore primarily an empirical one: to the best of my knowledge, no one has applied this framework to gauge asymmetric correlations in currencies sorted by their characteristics, and to study how the time-varying hedging benefits of currencies affect the optimal asset allocation of an international investor.

In this paper, the simple structure of the model helps to illustrate my findings in a clear-cut way. But this framework can be extended to examine other important issues. For example, instead of considering (one-period) mean-variance utility, one can allow for investors with preferences on higher moments and with longer horizons. To do so, one could follow Guidolin and Timmermann (2008), who consider the optimal allocation over international equities of an investor who takes into account skew and kurtosis preferences, allowing for regime switching. I leave this possible extension for future research.

The remainder of the paper is organized as follows. In the next section I describe the data and define how I form the currency portfolios sorted by a number of characteristics. Section 3 describes the econometric model and the estimation procedure, and presents the empirical results. In Section 5 I outline the portfolio choice problem and report the estimated allocations. Finally, Section 6 concludes.

2 Data and Portfolio Construction

2.1 Data

I use a cross section of nominal spot and one-month forward exchange rates by collecting data on 48 currencies relative to the US dollar: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom.

The sample period runs from November 1983 to September 2011. I convert daily data into non-overlapping monthly observations by sampling on the last business day of each month. Note that the number of exchange rates for which there are available data varies over time. The data are collected by WM/Reuters and Barclays and are available on Thomson Financial Datastream.

The data on IIP come from the updated Lane and Milesi-Ferretti (2007) dataset on the External Wealth of Nations, covering the years 1982 to 2010.[2] Data on the current account, PPP conversion factors, and GDP are from the IMF's World Economic Outlook database. For the PPP conversion factors, the IMF sources their data from the International Comparison Programme (ICP). When ICP data are not available for any country, the IMF provide their own estimate of the PPP conversion factor (in my sample, this is the case for Taiwan).

2.2 Returns

The excess return on foreign exchange is defined as the return of investing on a foreign riskless bond and funding the position by borrowing in local currency. [3] The excess returns on foreign exchange is then equal to the interest rate differential plus the depreciation of the domestic currency. We can therefore write the (one-period) excess return as

$$r_{j,t+1} = s_{j,t+1} - s_{j,t} + i^*_{j,t} - i_{j,t}, \tag{2.1}$$

for $j = \{1, ..., N_t\}$, where N_t is the number of exchange rates at time t; $s_{j,t}$ is the log of the nominal spot exchange rate defined as the domestic price of foreign currency j at time t; and $i^*_{j,t}$ and $i_{j,t}$ are the continuously compounded interest rates of foreign and domestic riskless bonds, respectively. Note that an increase in $s_{j,t+1}$ implies a depreciation of the domestic currency, namely the US dollar.

Under covered interest parity (CIP) the interest rate differential is equal to the forward discount, i.e. $i_t - i^*_{j,t} = f_{j,t} - s_{j,t}$, where $f_{j,t}$ is the log of the one-period forward exchange rate j at time t, which is the rate agreed at time t for an exchange of currencies at $t+1$.[4] Therefore, we can rewrite Equation (2.1) as

$$r_{j,t+1} = s_{j,t+1} - f_{j,t}. \tag{2.2}$$

This excess return is equivalent to the return of buying a forward contract now for exchanging the domestic currency into foreign currency in the future, and converting the proceeds of the forward

[2] I thank Philip Lane and Gian Maria Milesi-Ferretti for kindly providing an updated version of their dataset.

[3] For ease of exposition, and as is usual in the exchange rates literature, I use the notation in terms of log returns, but I use discrete returns in the empirical analysis that follows, as is customary in the analysis portfolio returns to avoid problems with Jensen's inequality terms (see, e.g., Campbell et al., 1997).

[4] There is ample empirical evidence that CIP holds in practice for the data frequency examined in this paper. For recent evidence, see Akram et al. (2008). The only exception in my sample is the period following Lehman's bankruptcy, when the CIP violations persisted for a few months (e.g., Mancini-Griffoli and Ranaldo, 2011). Using a similar dataset to mine, Lustig et al. (2011) argue that CIP deviations can be safely regarded as measurement error: they report an estimated 126 basis points deviation during the crisis (from Jones, 2009), which is small compared to the large average returns of the currency strategies during the 28 years of my sample.

contract into the domestic currency at the future spot exchange rate. Under risk neutrality, the expected excess return would be equal to zero, a hypothesis also known as uncovered interest parity (UIP). However, UIP is strongly rejected by the data, a result that is usually explained by appealing to time-varying risk premia, expectational errors, or some form of investors heterogeneity (see, e.g., Fama, 1984; Engel, 1996; Bacchetta and van Wincoop, 2010).

Empirically, and consistently with most literature, I calculate returns using Equation (2.2) as opposed to Equation (2.1) because of the much wider availability, both in terms of cross-sectional and time-series dimensions, of forward rates rather than interest rates.

2.3 Portfolios

I analyse five sets of portfolios of currencies, grouped according to different currency characteristics. This approach focuses attention on currency characteristics, and away from the idiosyncrasies of individual exchange rates (see Lustig and Verdelhan, 2007). I focus on the following characteristics : (i) the interest rate of a currency relative to that of the US dollar; (ii) momentum, i.e. currency's past performance; (iii) the undervaluation of the exchange rate relative to PPP; (iv) the net international investment position and (v) current account, as a ratio to GDP, of the country where the currency is legal tender.

I implement the currency strategies as follows. At the end of each month, I form quintile portfolios of currencies based on the characteristics prevailing in that month. The portfolios are then held for one month and I calculate the holding-period return as the average of the currency excess returns in each portfolio. Carry and Momentum portfolios are rebalance monthly, whereas the other portfolios are rebalanced annually because data on CA, IIP, and PPP conversion factors are available only at an annual frequency.

For example, in the case of portfolios sorted by forward discounts, I allocate the one fifth of currencies that have the lowest interest rate (highest forward discount) relative to the US dollar to the first portfolio (P1), the next fifth to the second portfolio (P2), and so on until the one fifth of currencies with the highest interest rate are allocated to the fifth portfolio (P5). I also analyse the properties of the "high-minus-low" portfolio (HML) that invests in P1 and shorts P5. I form all the other groups of portfolios in a similar fashion, by sorting currencies on the other currency characteristics. More specifically, I identify the currency characteristics based on the following "signals":

Carry: the forward discount (or, equivalently, the interest rate differential) of a currency relative to the US dollar. Lustig and Verdelhan (2007) were the first to sort currencies by their forward discounts to build portfolios, followed suit by Lustig et al. (2011) and Menkhoff et al. (2012a).

Momentum: the past 12-month cumulative return of the currency, as in Menkhoff et al. (2012b).

Value: the under/overvaluation relative to the level implied by PPP. Defining the (log) real exchange as $q_t = s_t + p_t^* - p_t$, where p_t^* and p_t are the logs of foreign and domestic price indices, respectively, absolute PPP implies that $q_t = 0$. When q_t is greater than zero, then the foreign currency is overvalued in real terms. Clearly, this is only a rough measure of currency "fair value", but has a number of desirable features: (i) it lets me build the portfolios in an out-of-sample fashion; (ii) it mimics several trading strategies used in the financial industry (see, e.g., Deutsche Bank, 2007); (iii) it does not involve any econometric estimation, therefore avoiding the problem of introducing estimation error in the analysis.[5] I sort currencies from most overvalued to most undervalued relative to PPP. Rafferty (2011) builds portfolios in a similar fashion.

IIP: the net international investment position, as a ratio to GDP, of the country where the currency is legal tender. I sort currencies from high IIP (net-creditor countries) to low IIP (net-debtor countries). Della Corte et al. (2012) form portfolios in a similar fashion.

CA: the current account, as a ratio to GDP, of the country where the currency is legal tender. I sort currencies from high CA (countries with high current account surpluses) to low CA (countries with high current account deficits).

3 Model Description

I model currency portfolio returns using a model inspired by the zero-beta CAPM of Black (1972) in an international setting. The zero-beta representation of the CAPM allows to deal with the absence of a risk-free asset. The world CAPM implies that the expected return on any asset is linear in its exposure (beta) to the world-market risk factor, that is

$$r_t^i = \mu^z + \beta^i(\mu^w - \mu^z) + \beta^i \sigma^w \epsilon_t^w + \sigma^i \epsilon_t^i, \quad (3.1)$$

$$r_t^w = \mu^w + \sigma^w \epsilon_t^w, \quad (3.2)$$

[5] For a survey of other more sophisticated measures of currency fair value, see Cenedese and Stolper (2012).

where r^i is the return on currency portfolio i and σ^i is its (idiosyncratic) volatility; μ^w is the expected return on the world equity market and σ^w is its conditional volatility; ϵ^w and ϵ^i are the world market shock and idiosyncratic Gaussian shocks, respectively; β^i measures the exposure of portfolio i to market risk; finally, μ^z denotes the zero-beta return, that is, the return on the portfolio that has the minimum variance among all the portfolios uncorrelated with the market.[6]

I extend this model by allowing the world equity market to switch between a "normal" and "crisis" regime, using a model that belongs to the popular Markov regime-switching class of models of Hamilton (1989). The economic intuition behind the regime switching is that international equity markets could be driven by a world business cycle, which shifts between expansions and recessions.[7] More specifically, I model the regimes as a discrete variable that can take on two values, $s_t \in \{1, 2\}$, that governs the shift from a regime to the other. Model (3.1)–(3.2) then becomes

$$r_t^i = \mu^z + \beta^i(\mu_{s_t}^w - \mu^z) + \beta^i \sigma_{s_t}^w \epsilon_t^w + \sigma^i \epsilon_t^i, \quad (3.3)$$

$$r_t^w = \mu_{s_t}^w + \sigma_{s_t}^w \epsilon_t^w. \quad (3.4)$$

This model therefore allows the probability distribution of the world market to assume different means and volatilities, conditional on the realisation of the regime variable s_t. Given the dependence of the currency portfolio returns on the the world market expected return, the model, though parsimonious, generates rich patterns of time-varying returns, volatilities, and asymmetric correlations. Ang and Bekaert (2004) apply a similar model to the study of international equity markets.

Also, Markov-switching models such as the one considered here can capture key statistical features of asset returns such as asymmetric distributions and fat tails. One can see these models as a generalisation of time-independent mixture of normals models; Timmermann (2000) derives the moments for a number of Markov-switching models and shows how they can generate a wide range of coefficients of skewness, kurtosis and serial correlation even when based on a very small number of underlying states.

To complete the specification of the model, it is necessary to describe the data generating process for the latent variable s_t. The variable s_t follows a first-order Markov chain with transition

[6] As in all the econometric analyses of the zero-beta CAPM, I treat the zero-beta portfolio as an unobserved quantity, that is, an unobserved model parameter to be estimated.

[7] It may be conceivable that country-specific, idiosyncratic regimes drive the world market, but I don't allow for this in the specification of the model.

probabilities

$$\begin{aligned}
\Pr(s_t = 1|s_{t-1} = 1) &= P, \\
\Pr(s_t = 2|s_{t-1} = 1) &= 1 - P, \\
\Pr(s_t = 2|s_{t-1} = 2) &= Q, \\
\Pr(s_t = 1|s_{t-1} = 2) &= 1 - Q,
\end{aligned}$$

that is, the probabilities of going from one regime to the other depend only on the previous regime and are constant over time. This feature of the model allows mixing probabilities to display time dependence in a very parsimonious way and can capture the time dependence in the conditional variance that is present in many economic time series.

3.1 Estimation

We can rewrite the model in vector notation in the form of a factor model,

$$\underbrace{\begin{bmatrix} r_t^w \\ r_t^1 \\ \vdots \\ r_t^5 \end{bmatrix}}_{R_t} = \underbrace{\begin{bmatrix} 0 \\ \mu^z(1-\beta^1) \\ \vdots \\ \mu^z(1-\beta^5) \end{bmatrix}}_{\alpha} + \underbrace{\begin{bmatrix} 1 \\ \beta^1 \\ \vdots \\ \beta^5 \end{bmatrix}}_{B} \mu_{s_t}^w + \Sigma_{s_t}^{1/2} \underbrace{\begin{bmatrix} \epsilon_t^w \\ \epsilon_t^1 \\ \vdots \\ \epsilon_t^5 \end{bmatrix}}_{\epsilon_t}, \tag{3.5}$$

where the covariance matrix of the innovations is given by

$$\Sigma_{s_t} = [\sigma_{s_t}^w]^2 BB' + \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_1^2 & 0 & \cdots & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_5^2 \end{bmatrix}.$$

Let θ denote the vector of parameters of the likelihood function for the data. Given that the innovations are Gaussian, the density conditional on being in state j is also Gaussian:

$$f(R_t|\Omega_{t-1}, s_t = j; \theta) = (2\pi)^{-3}|\Sigma_j|^{-1/2} \exp[(-1/2)(R_t - \alpha - B\mu_j^w)'\Sigma_j^{-1}(R_t - \alpha - B\mu_j^w)], \tag{3.6}$$

for $j = 1, 2$, and where Ω_{t-1} denotes the information set available at time $t-1$. The log-likelihood takes the form

$$\ell(\theta) = \sum_{t=1}^{T} \ln(f(R_t|\Omega_{t-1};\theta)), \tag{3.7}$$

where the density $f(R_t|\Omega_{t-1};\theta)$ is obtained by summing the probability-weighted densities across the two possible regimes:

$$f(R_t|\Omega_{t-1};\theta) = \sum_{j=1}^{2} f(R_t|\Omega_{t-1}, s_t = j;\theta)\,\Pr(s_t = j|\Omega_{t-1};\theta), \tag{3.8}$$

where $\Pr(s_t = j|\Omega_{t-1};\theta)$ is the probability of being in state j at time t, conditional on information at time $t-1$. Hamilton (1994) shows that the conditional state probabilities $\Pr(s_t = i|\Omega_{t-1};\theta)$ can be obtained recursively by iterating the following two equations, which follow directly from the total probability theorem and Bayes' rule:

$$\Pr(s_t = i|\Omega_{t-1};\theta) = \sum_{j=1}^{2} \Pr(s_t = i|s_{t-1=j}, \Omega_{t-1};\theta)\,\Pr(s_{t-1} = j|\Omega_{t-1};\theta) \tag{3.9}$$

$$\Pr(s_{t-1} = j|\Omega_{t-1};\theta) = \frac{f(R_{t-1}|s_{t-1} = j;\theta)\,\Pr(s_t = j|\Omega_{t-1};\theta)}{\sum_{j=1}^{2} f(R_t|s_t = j;\theta)\,\Pr(s_t = j;\theta)}. \tag{3.10}$$

The log-likelihood is then obtained as a byproduct of this procedure, and can be maximised using standard numerical algorithms (see, e.g., Hamilton, 1994, Chapter 5).

4 Empirical Results

4.1 Descriptive Statistics

I report descriptive statistics of the portfolio returns based on all the available countries in Table 1. The table presents results for portfolios P1 to P5 grouped by each characteristic at a time: (i) the interest rate of a currency relative to that of the US dollar; (ii) momentum, i.e. currency's past performance; (iii) the undervaluation of the exchange rate relative to PPP; (iv) the net international investment position and (v) current account, as a ratio to GDP, of the country where the currency is legal tender. The results for the HML portfolios are reported in the bottom right of the table. The statistical properties of the portfolio returns are in line with those reported in the literature.[8]

Sorting currencies by interest rates or momentum creates a large average spread between the

[8] See, e.g., Lustig et al., 2011; Rafferty, 2011; Menkhoff et al., 2012a,b; Della Corte et al., 2012.

returns on portfolios P1 and P5: the return on the HML carry and HML momentum portfolios are more than nine and five per cent annualised, respectively. Sorting currencies by other characteristics yields similar patterns, that is, average excess returns are almost monotonic. For example, undervalued currencies tend to provide higher average returns than overvalued currencies, as is the case for net-creditor (as measured by their IIP) currencies relative to net-debtor ones. Therefore, these results suggest that average returns vary across currency portfolios. A central economic question is to understand why, given that different expected returns should reflect different risk exposures. The papers cited in the introduction try to answer this question by identifying a number of possible risk factors. In this paper, I am more interested in understanding how the risk exposures to the world equity market can change over time, and what this implies for the optimal allocation of investors' wealth.

Standard deviations are roughly similar across portfolios for each characteristic analysed. Taken together with the almost monotonic pattern of average excess returns, this explains the almost monotonicity of Sharpe ratios, a measure of risk-adjusted returns. The Sharpe ratios for the HML portfolios range from 0.43 for the HML^{VAL} and HML^{IIP} portfolios, to 0.97 for HML^{Carry}. The latter is in particular consistent with the literature on the very high risk-adjusted returns of carry trade strategies relative to the equity market (see, e.g., Burnside et al., 2008, and the papers cited in the introduction). Autocorrelation in returns tend to be small for all portfolios and statistically significant only for 9 out of 30 portfolios at the 5% confidence level.

The distribution of portfolio returns display asymmetry and fat tails: skewness is negative for most portfolios (26 out of 30) and kurtosis is relatively high compared to the normal distribution for all portfolios. This pattern is particularly strong when looking at the HML portfolios, with the exception of HML^{CA}, which shows values of skewness and kurtosis that are closer to those implied by the normal distribution. Taken together, these results provide further motivation for the use of a regime-switching model as in the framework adopted in this paper, as highlighted in the introduction.

Following Lustig et al. (2011) and Menkhoff et al. (2012a), I also report results for a subsample of 15 developed countries. This sample comprises: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. After the adoption of the euro, this subsample reduces to 10 currencies. Table 2 presents descriptive statistics for the portfolios using this subsample of countries. The qualitative results are the same as those reported for all countries, with the exception that they display weaker evidence of monotonic patterns in average excess returns for a number of currency characteristics (in particular, momentum). Standard deviations tend to be higher than the case using all countries because of the reduced degree of diversification.

4.2 Estimation Results of the Regime-switching Models

Table 3 presents the parameter estimates of the regime-switching model specified in Equations (3.3)–(3.4). To save space, here and in subsequent sections I focus on the results using the sample based on all countries available. Results based on the subsample of developed countries only are not qualitatively different, and are available upon request. In order to keep the model parameters to a minimum, I estimate the model separately for each currency characterstics. That is, I estimate the equation for world equity market jointly with the equations for the returns of portfolio P1 to P5 for for interest-rate sorted portfolios, then I do the same for the momentum sorted portfolios, and so on. Because of the joint estimation, the parameters of the equation for the world equity market can slightly differ across currency characteristics. However, Table 3 shows that the first regime can be characterised as a "tranquil" bull market, in which the world equity market yields an expected monthly return of more than 1.6 per cent, with volatility about 3 per cent a month. In contrast, the other regime can be characterised as a volatile bear regime with an expected monthly return of about -2 per cent, and volatility of almost 6 per cent a month. The monthly transition probabilities of the regimes, P and Q, are close to one, indicating persistence in the regimes. The probability that a tranquil world market will be followed by another month of tranquil market is about $P = 0.95$, so that this regime will persist on average for $\frac{1}{(1-P)} = 20$ months. The probability that a volatile bear world market will be followed by another month of bear market is about $Q = 0.85$, so that this regime will persist on average for about $\frac{1}{(1-Q)} = 6.7$ months. Therefore, as one would expect, times of financial stress characterized by the second regime are short-lived relative to normal periods.

Figure 1 displays the smoothed probabilities of being in the first, tranquil regime.[9] The smoothed probability is the probability, given all of the information present in the data sample, that the regime in a given month is the low-volatility, high-mean regime. I compute this probability for each month using the algorithm developed by Kim (1994). These probabilities seem to identify well widely recognised periods of financial markets turbulence: in 1987 for a very short period, during the Asian crisis of 1997, the 2000s burst of the dot-com bubble, and during the most recent global financial crisis.

[9] The smoothed probability of the figure refers to the estimation using the interest-rate sorted portfolios. The smoothed probabilities for the specifications focusing on different characteristics are virtually identical.

The betas tend to be monotonically increasing across different characteristics. For the "low" portfolios (P1 and P2), the betas tend to be imprecisely estimated, but the monotonic patterns are consistent across different characteristics. Therefore, "high" portfolios tend to have higher risk exposures to the world equity market relative to the low portfolios. Idiosyncratic volatilities are roughly similar in all specifications, with an average of 2.5 per cent a month across specifications.

Table 4 presents the correlations across regimes as implied by the model. Given the factor-structure of the model, and given that the second regime is a high-volatility regime, the model is expected to generate correlations between the currency portfolios and the world equity market that are higher in the second regime. In fact, the table shows this asymmetric correlation pattern across all the specifications. Here, the important empirical result is to see how the correlations depend on different currency characteristics. For example, high-interest rate currencies have, in the bear market regime, a correlation with the world market that is about four times larger than in the normal market regime. Instead, the correlation of low-interest rate currencies with the world market barely changed and, if anything, they slightly decrease in during bear markets. Analogous behaviour can be seen when focusing on other characteristics. For example, high-momentum currencies increase their correlation by more than seven times in bear markets.

5 Asset Allocation

To focus on the effects of the presence of regimes on the optimal portfolio choice, I follow Ang and Bekaert (2004) and use a mean-variance optimization with monthly rebalancing, consistent with the data frequency.[10] This framework is simple and provides a closed-form solution of the optimal asset allocation problem, letting me focus on the regime shifts. The investor maximizes the utility function:

$$\max_{\omega} E(r_{p,t+1}) - \frac{\gamma}{2}\operatorname{var}(r_{p,t+1}), \tag{5.1}$$

where $r_{p,t+1}$ is the return on a combination of currency portfolios P1, P2, ..., P5; γ measures the investor's level of relative risk aversion; ω denotes the vector of weights in each currency portfolio, and $E(R)$ is vector of expected returns of model (3.5), conditional on regime j. The optimal mean-

[10] Time-varying opportunity sets, like in this paper, may affect the optimal asset allocation of investors with different horizons. However, Ang and Bekaert (2002) show that the differences with a standard mean-variance optimal allocation are not large.

variance weights for each regime j are:

$$\omega_j = \frac{1}{\gamma}\Sigma_j^{-1}E_j(R). \tag{5.2}$$

The Markov-switching model delivers two tangency portfolios, one for each regime. I focus on these two tangency portfolio because they do not depend on the risk-free rate or coefficient of risk aversion. The tangency portfolios, conditional on being in regime j, are given by

$$\overline{\omega}_j = \frac{\Sigma_j^{-1}E_j(R)}{\iota'\Sigma_j^{-1}E_j(R)}, \tag{5.3}$$

where ι is a vector of ones.

5.1 Asset Allocation Results

Table 5 reports the tangency portfolio weights when focusing on currency characteristics. The optimal weights for the first and second regimes are computed using the estimated expected returns, volatilities, and correlations of model (3.3)–(3.4). The third column in each panel shows the unconditional weights, that is, the optimal weights ignoring the presence of different regimes. I compute the unconditional weights using the unconditional moments as implied by the model. Unconditional expected returns are a weighted average of the conditional expected returns, with the weights equal to the ergodic (unconditional) probabilities of the Markov chain. The variance is not simply the average of the variances across the two regimes: the difference in means also imparts an effect because the switch to a new regime contributes to volatility. Intuitively, the possibility of changing to a new regime with a different mean introduces an extra source of risk.[11]

Figures 2 and 3 illustrate the mean-variance optimal allocation among interest-rate sorted currency portfolios. The figure shows the frontier of regime 1 (the tranquil regime), regime 2 (the bear market regime), and the unconditional mean-variance frontier, which averages across the two regimes. One can clearly see that the efficient frontier ignoring the presence of the two regimes can be very different from the one in framework acknoledging the existence of difference regimes.

In most cases, the optimal allocation in the tranquil regime is close to a balanced, equally weighted strategy. Given that this is the most persistent regime, the result echoes the finding by DeMiguel et al. (2009) that equally weighted portfolios typically outperform more complex strategies. In the case of carry-sorted portfolios, this strategy is similar to the dollar factor of Lustig et al. (2011) or

[11] For the exact formulas, see Timmermann (2000).

the 'dollar carry trade' of Lustig et al. (2012), that is, an equally weighted long position in a basket of foreign currencies and a short position in the US dollar.

The high-volatility bear market regime is characterised by a significant shift in the optimal allocations. Notably, when focusing on carry, an investor would be best off by allocating more than 50 per cent of her wealth in low-interest-rate currencies (portfolio P1), and going short high-interest rate currencies (portfolio P5). This result echoes the finding that international investors tend to unwind their carry trade positions during periods of financial turmoil (see, e.g., Brunnermeier et al., 2009). An analogous result holds for IIP-sorted portfolios: the optimal allocation tells the investor to put more than 70 per cent of her wealth in currencies of net-creditor countries, and short the currencies of net-debtors. Also, an investor should hold currencies of countries with stronger current accounts in bad times, and short currencies of countries with weaker current accounts. The optimal portfolios for momentum and value-sorted currencies appear more stable across regimes.

The last panel of Table 5 shows the optimal mean-variance allocation across all HML portfolios. In the tranquil regime, an investor would optimally choose a relatively well-balanced portfolio, but with the highest weights allocated to the IIP HML portfolio, which goes long on net-debtor countries and short on net-creditor countries, and the CA HML portfolio, which goes long on countries with high CA deficits and shorts on countries with high CA surpluses. In contrast, in the second regime the investor is better off by reallocating her portfolio holdings dramatically. More specifically, the investor would allocate almost 50 per cent of her wealth to the Value HML portfolio, which goes long undervalued currencies and shorts overvalued currencies, and the Momentum HML portfolio, which goes long on past-winner currencies and short on past-loser currencies. It is interesting to notice that also in this case it is also optimal to unwind carry trade positions in crisis times: the optimal weight on the Carry HML portfolio (long on high-interest rate currencies and short on low-interest rate currencies) is close to zero. Also, external sustainability seem to matter, regardless of whether one takes a flow or stock perspective: the weights on the CA HML and IIP HML portfolios are also close to zero, meaning that is optimal to unwind positions on currencies with weak external balances and investing in currencies with strong external balances.

6 Conclusions

This paper finds that the foreign exchange market exhibits asymmetric correlations: during periods of bear, volatile world equity markets, currency portfolios provide different hedging benefits than in bull markets. The model can generate correlations between the currency portfolios and the world equity market that are higher in bear markets. I show how these time-varying hedging benefits depend on currency characteristics. For example, high-interest rate currencies have, in the bear market regime, a correlation with the world market that is about four times larger than in the normal market regime. Instead, the correlation of low-interest rate currencies with the world market barely changed and, if anything, they slightly decrease in during bear markets. Analogous behaviour can be seen when focusing on other characteristics. With the estimates of the econometric model at hand, I show how the time-varying opportunity set translates into an optimal asset allocation of investors' wealth. In most cases, the optimal allocation in the tranquil regime is close to a balanced, equally weighted strategy. Notably, when focusing on carry, an investor would be better off by allocating more than 50 per cent of her wealth in low-interest-rate currencies, and going short high-interest rate currencies. An analogous result holds for IIP-sorted portfolios.

In this paper, the simple structure of the model helps to illustrate my findings in a clear-cut way. But this framework can be extended to examine other important issues. For example, instead of considering (one-period) mean-variance utility, one can allow for investors with preferences on higher moments and with longer horizons. To do so, one could follow Guidolin and Timmermann (2008), who consider asset allocation over international equities with a regime switching model by an investor who takes into account skew and kurtosis preferences.

Figure 1: **Probability of Being in the Tranquil Regime (1)**

The figure displays smoothed probabilities that the world equity market is in the tranquil regime (Regime 1). The smoothed probability is the probability, given all of the information present in the data sample, that the regime in a given month is the low-volatility, high-mean regime. I compute this probability for each month using the algorithm developed by Kim (1994).

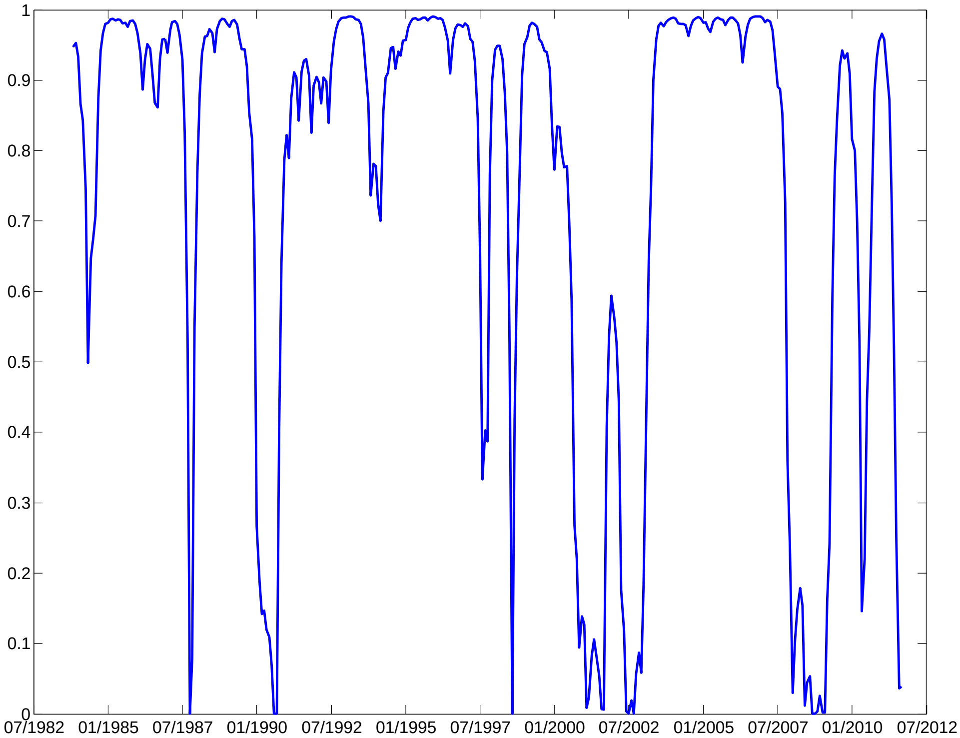

Figure 2: **Mean-Standard Deviation Frontiers using Carry portfolios**

The figure illustrates the mean-variance optimal allocation among interest-rate sorted currency portfolios. The figure shows the frontier of regime 1 (the tranquil regime), regime 2 (the bear market regime), and the unconditional mean-variance frontier, which averages across the two regimes.

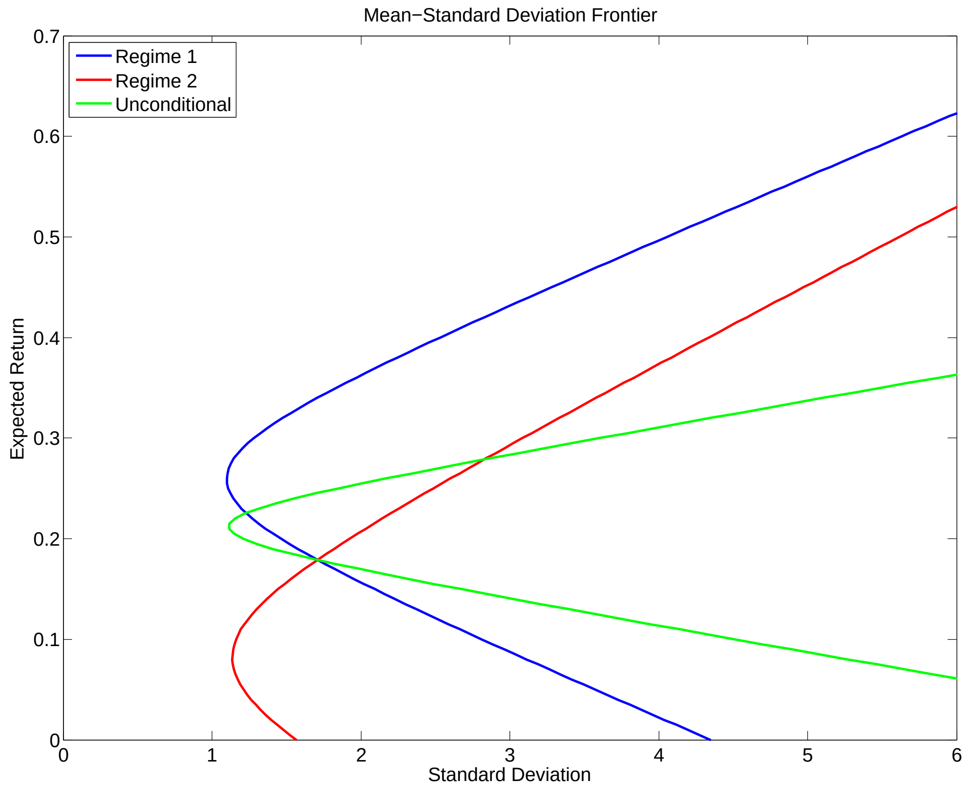

Figure 3: **Mean-Standard Deviation Frontiers using HML portfolios**

The figure illustrates the mean-variance optimal allocation among all HML currency portfolios. The figure shows the frontier of regime 1 (the tranquil regime), regime 2 (the bear market regime), and the unconditional mean-variance frontier, which averages across the two regimes.

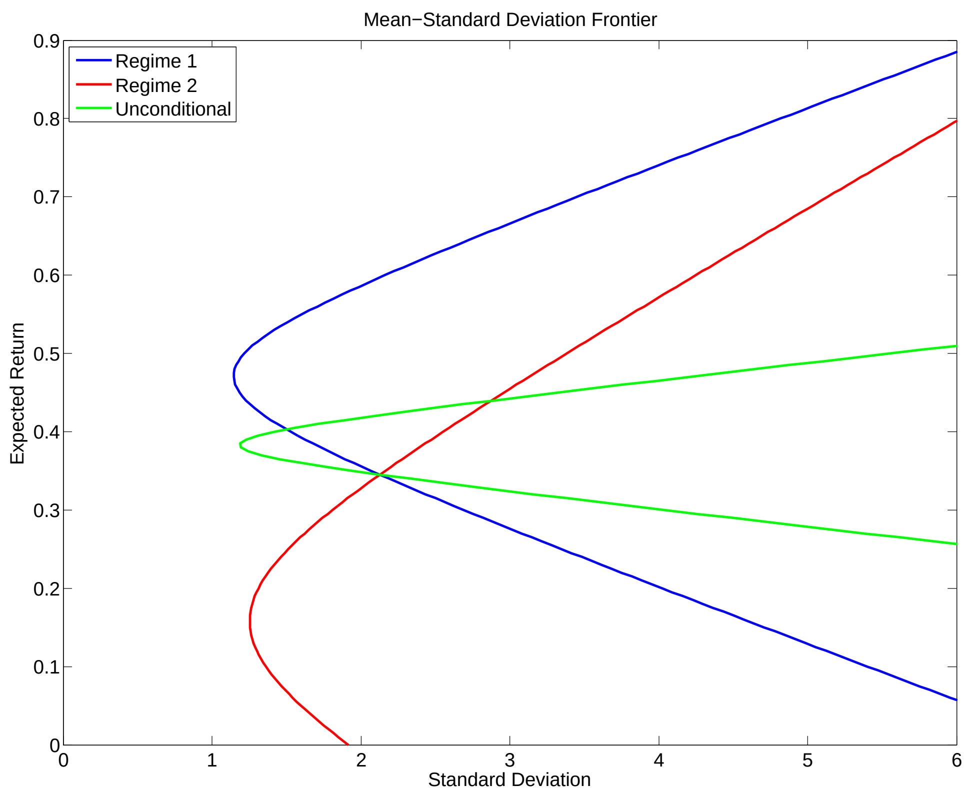

Table 1: Descriptive Statistics of Portfolio Returns: All Countries

The table reports descriptive statistics for the monthly returns of the currency portfolios sorted by a number of characteristics (signals), using all currencies available in my sample. The sample of 48 individual currencies runs from November 1983 to September 2011. Portfolio 1 (P1) contains the one fifth of currencies that have the lowest past signal, whereas portfolio 5 (P5) contains the country indices with the highest past signal. HML denotes the portfolio that is long on P5 and short on P1. The holding period is one month. Numbers in brackets show Newey and West (1987) t-statistics. AC(1) is the first-order autocorrelation. All figures are annualised, in percentage points.

	Carry					Momentum				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Mean	-0.95	0.88	3.77	4.46	7.65	2.05	2.73	3.37	5.09	7.26
	[-0.53]	[0.56]	[2.03]	[2.46]	[2.90]	[1.06]	[1.47]	[1.84]	[2.64]	[3.65]
Median	-1.45	1.48	2.78	5.07	11.28	1.78	3.21	3.42	4.45	6.96
Std. Dev.	8.30	7.36	8.22	8.49	10.52	9.64	8.38	8.50	8.87	8.68
Skewness	0.26	-0.11	-0.18	-0.43	-0.37	0.68	0.73	-0.31	-0.26	-0.47
Kurtosis	3.93	3.99	4.08	4.41	4.65	8.20	7.46	4.53	4.53	5.14
Sharpe Ratio	-0.11	0.12	0.46	0.53	0.73	0.21	0.33	0.40	0.57	0.84
AC(1)	0.04	0.08	0.13	0.10	0.22	0.11	0.05	0.06	0.12	0.15
	[0.55]	[1.26]	[2.19]	[1.30]	[2.63]	[1.13]	[0.77]	[0.81]	[1.67]	[1.99]
	Value					International Investment Position				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Mean	1.00	3.36	2.83	3.96	4.59	1.38	3.85	2.92	3.28	4.26
	[0.46]	[1.73]	[1.70]	[2.09]	[2.34]	[1.17]	[1.85]	[1.54]	[1.93]	[1.71]
Median	1.33	5.89	4.10	4.92	3.78	0.32	3.37	3.52	4.75	5.40
Std. Dev.	9.98	9.20	7.58	8.40	7.49	5.45	9.07	8.89	7.61	10.70
Skewness	-0.16	-0.06	0.01	-0.33	0.06	0.28	-0.01	-0.36	-0.56	-0.54
Kurtosis	3.58	3.71	5.08	4.42	5.77	4.47	3.59	3.96	4.85	5.11
Sharpe Ratio	0.10	0.36	0.37	0.47	0.61	0.25	0.43	0.33	0.43	0.40
AC(1)	0.14	0.04	0.13	0.05	0.22	0.05	0.12	0.08	0.17	0.14
	[2.25]	[0.67]	[1.86]	[0.84]	[2.64]	[0.63]	[2.14]	[1.21]	[2.14]	[1.71]
	Current Account					HML				
	P1	P2	P3	P4	P5	Carry	MOM	VAL	IIP	CA
Mean	1.11	2.38	3.65	4.72	4.06	9.05	5.21	3.48	3.24	3.84
	[0.75]	[1.26]	[2.29]	[2.10]	[1.80]	[4.03]	[2.53]	[1.89]	[2.07]	[2.15]
Median	1.20	2.89	3.74	4.45	5.87	11.47	7.36	6.24	4.45	3.64
Std. Dev.	6.68	8.80	7.71	9.29	9.83	9.35	10.47	8.08	7.59	8.57
Skewness	-0.07	-0.02	-0.39	-0.29	-0.45	-0.86	-0.57	-0.75	-0.46	-0.01
Kurtosis	3.67	4.73	4.97	4.71	5.32	4.75	4.92	5.29	3.87	3.06
Sharpe Ratio	0.17	0.27	0.47	0.51	0.41	0.97	0.50	0.43	0.43	0.45
AC(1)	0.07	0.07	0.09	0.26	0.10	0.18	0.01	0.17	0.10	0.11
	[1.01]	[1.18]	[1.25]	[3.11]	[1.31]	[2.23]	[0.19]	[1.92]	[1.40]	[1.85]

Table 2: Descriptive Statistics of Portfolio Returns: Developed Countries Only

The table reports descriptive statistics for the monthly returns of the currency portfolios sorted by a number of characteristics (signals), using a subsample of developed countries listed in the main text. The sample of 15 individual currencies runs from November 1983 to September 2011. Portfolio 1 (P1) contains the one fifth of currencies that have the lowest past signal, whereas portfolio 5 (P5) contains the country indices with the highest past signal. HML denotes the portfolio that is long on P5 and short on P1. The holding period is one month. Numbers in brackets show Newey and West (1987) t-statistics. AC(1) is the first-order autocorrelation. All figures are annualised, in percentage points.

	Carry					Momentum				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Mean	0.19	2.61	2.59	3.68	6.28	2.32	4.56	4.16	4.98	4.56
	[0.09]	[1.15]	[1.31]	[1.80]	[2.55]	[1.02]	[2.00]	[1.81]	[2.35]	[2.52]
Median	-0.38	3.06	3.67	3.65	6.29	3.23	3.80	5.49	4.82	4.48
Std. Dev.	9.77	10.10	9.40	9.63	11.03	10.08	10.69	10.11	10.34	9.61
Skewness	0.22	-0.04	-0.05	-0.45	-0.16	0.10	-0.03	-0.21	-0.27	-0.16
Kurtosis	3.41	3.47	3.74	4.96	4.50	4.84	5.19	3.70	4.31	4.16
Sharpe Ratio	0.02	0.26	0.28	0.38	0.57	0.23	0.43	0.41	0.48	0.47
AC(1)	0.02	0.09	0.10	0.09	0.15	0.13	0.06	0.12	0.06	0.03
	[0.34]	[1.59]	[1.73]	[1.49]	[2.24]	[2.55]	[0.98]	[1.92]	[0.98]	[0.41]
	Value					International Investment Position				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Mean	0.50	2.69	2.79	2.12	7.17	2.46	2.04	3.08	2.19	5.38
	[0.23]	[1.22]	[1.24]	[1.05]	[3.78]	[1.05]	[1.01]	[1.47]	[1.12]	[2.34]
Median	1.02	4.65	3.99	3.47	6.23	0.98	2.54	3.83	4.13	6.23
Std. Dev.	10.26	10.62	9.75	9.67	8.98	11.19	9.61	9.82	8.88	10.39
Skewness	-0.23	-0.03	-0.23	-0.05	0.08	0.01	0.09	-0.25	-0.33	-0.32
Kurtosis	3.50	2.97	4.48	4.85	3.56	3.31	3.18	3.87	4.13	5.55
Sharpe Ratio	0.05	0.25	0.29	0.22	0.80	0.22	0.21	0.31	0.25	0.52
AC(1)	0.14	0.05	0.13	0.05	-0.02	0.08	0.02	0.08	0.10	0.09
	[2.44]	[0.84]	[2.34]	[0.66]	[-0.29]	[1.48]	[0.43]	[1.20]	[1.79]	[1.24]
	Current Account					HML				
	P1	P2	P3	P4	P5	Carry	MOM	VAL	IIP	CA
Mean	2.48	2.63	2.49	2.15	5.24	5.93	2.24	2.64	2.65	6.60
	[1.02]	[1.23]	[1.29]	[1.05]	[2.24]	[2.76]	[1.17]	[1.40]	[1.47]	[4.13]
Median	0.98	2.44	3.04	4.58	5.92	8.96	6.91	3.64	2.84	8.52
Std. Dev.	11.33	10.02	9.59	9.13	10.37	10.26	10.43	9.82	9.78	8.41
Skewness	-0.14	0.15	-0.30	-0.26	-0.30	-0.82	-0.19	-0.26	-0.29	-0.38
Kurtosis	3.35	3.38	4.12	4.35	5.45	5.32	5.06	3.57	3.36	3.79
Sharpe Ratio	0.22	0.26	0.26	0.24	0.50	0.58	0.21	0.27	0.27	0.78
AC(1)	0.10	0.06	0.06	0.14	0.09	0.11	0.02	0.00	0.02	0.03
	[1.56]	[1.15]	[1.11]	[2.06]	[1.30]	[1.42]	[0.34]	[0.07]	[0.26]	[0.47]

Table 3: Model Parameters

The table presents the estimates of the parameters of model (3.3)–(3.4) in the main text for currency portfolios sorted by their characteristics. Parameters are estimated using maximum likelihood assuming normally distributed returns in each regime. White's heteroskedasticity consistent standard errors are in parentheses. The sample of 48 individual currencies runs from November 1983 to September 2011.

	Carry		Momentum		Value		IIP		CA		HML	
$\mu^w(1)$	1.62	(0.22)	1.64	(0.22)	1.62	(0.22)	1.62	(0.22)	1.62	(0.22)	1.64	(0.22)
$\mu^w(2)$	-1.94	(1.07)	-1.96	(1.03)	-1.94	(1.11)	-1.94	(1.12)	-1.94	(1.11)	-1.96	(1.12)
$\sigma^w(1)$	2.98	(0.21)	2.95	(0.20)	2.98	(0.22)	2.98	(0.22)	2.98	(0.22)	2.95	(0.21)
$\sigma^w(2)$	5.88	(0.52)	5.89	(0.52)	5.88	(0.52)	5.88	(0.52)	5.88	(0.52)	5.88	(0.52)
P	0.95	(0.02)	0.95	(0.02)	0.95	(0.02)	0.95	(0.02)	0.95	(0.02)	0.95	(0.02)
Q	0.85	(0.06)	0.86	(0.06)	0.85	(0.06)	0.85	(0.06)	0.85	(0.06)	0.86	(0.06)
μ_z	0.18	(0.06)	0.31	(0.07)	0.24	(0.06)	0.19	(0.06)	0.21	(0.06)	0.35	(0.07)
β_1	-0.01	(0.03)	0.12	(0.04)	0.04	(0.03)	0.00	(0.02)	0.00	(0.02)	0.17	(0.03)
β_2	0.04	(0.03)	0.04	(0.03)	0.04	(0.03)	0.01	(0.03)	0.02	(0.03)	-0.01	(0.03)
β_3	0.07	(0.03)	0.06	(0.03)	0.07	(0.03)	0.07	(0.03)	0.08	(0.03)	0.17	(0.03)
β_4	0.10	(0.03)	0.04	(0.03)	0.13	(0.03)	0.12	(0.03)	0.11	(0.03)	0.16	(0.03)
β_5	0.16	(0.04)	0.12	(0.03)	0.08	(0.03)	0.17	(0.04)	0.17	(0.04)	0.03	(0.04)
σ_1	2.41	(0.09)	2.73	(0.11)	2.87	(0.11)	1.57	(0.06)	1.93	(0.07)	2.63	(0.10)
σ_2	2.12	(0.08)	2.41	(0.09)	2.65	(0.10)	2.62	(0.10)	2.53	(0.10)	3.02	(0.12)
σ_3	2.35	(0.09)	2.44	(0.10)	2.16	(0.08)	2.55	(0.10)	2.20	(0.08)	2.22	(0.09)
σ_4	2.42	(0.09)	2.55	(0.10)	2.36	(0.09)	2.14	(0.08)	2.65	(0.10)	2.08	(0.08)
σ_5	2.99	(0.12)	2.46	(0.10)	2.14	(0.08)	3.00	(0.12)	2.75	(0.11)	2.47	(0.10)

Table 4: Correlations

The table shows the estimates of the correlation matrices implied by model (3.3)–(3.4) in the main text for currency portfolios sorted by their characteristics. Parameters are estimated using maximum likelihood assuming normally distributed returns in each regime. The sample of 48 individual currencies runs from November 1983 to September 2011.

Carry Regime 1

	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.329	-0.136	-0.060	0.001	0.106
P1	-0.329	1.000	-0.231	-0.244	-0.254	-0.258
P2	-0.136	-0.231	1.000	-0.247	-0.248	-0.237
P3	-0.060	-0.244	-0.247	1.000	-0.240	-0.226
P4	0.001	-0.254	-0.248	-0.240	1.000	-0.216
P5	0.106	-0.258	-0.237	-0.226	-0.216	1.000

Carry Regime 2

	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.368	0.070	0.215	0.324	0.434
P1	-0.368	1.000	-0.299	-0.333	-0.355	-0.359
P2	0.070	-0.299	1.000	-0.236	-0.213	-0.173
P3	0.215	-0.333	-0.236	1.000	-0.153	-0.101
P4	0.324	-0.355	-0.213	-0.153	1.000	-0.044
P5	0.434	-0.359	-0.173	-0.101	-0.044	1.000

Momentum Regime 1

	y^w	P1	P2	P3	P4	P5
y^w	1.000	0.018	-0.179	-0.138	-0.178	0.061
P1	0.018	1.000	-0.244	-0.241	-0.243	-0.223
P2	-0.179	-0.244	1.000	-0.239	-0.235	-0.250
P3	-0.138	-0.241	-0.239	1.000	-0.238	-0.246
P4	-0.178	-0.243	-0.235	-0.238	1.000	-0.250
P5	0.061	-0.223	-0.250	-0.246	-0.250	1.000

Momentum Regime 2

	y^w	P1	P2	P3	P4	P5
y^w	1.000	0.332	-0.033	0.056	-0.039	0.433
P1	0.332	1.000	-0.242	-0.208	-0.243	-0.047
P2	-0.033	-0.242	1.000	-0.272	-0.274	-0.234
P3	0.056	-0.208	-0.272	1.000	-0.271	-0.192
P4	-0.039	-0.243	-0.274	-0.271	1.000	-0.236
P5	0.433	-0.047	-0.234	-0.192	-0.236	1.000

IIP Regime 1

	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.282	-0.256	-0.102	0.113	0.125
P1	-0.282	1.000	-0.210	-0.236	-0.275	-0.255
P2	-0.256	-0.210	1.000	-0.236	-0.271	-0.251
P3	-0.102	-0.236	-0.236	1.000	-0.246	-0.230
P4	0.113	-0.275	-0.271	-0.246	1.000	-0.196
P5	0.125	-0.255	-0.251	-0.230	-0.196	1.000

IIP Regime 2

	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.265	-0.218	0.113	0.534	0.460
P1	-0.265	1.000	-0.228	-0.296	-0.350	-0.320
P2	-0.218	-0.228	1.000	-0.289	-0.324	-0.298
P3	0.113	-0.296	-0.289	1.000	-0.139	-0.142
P4	0.534	-0.350	-0.324	-0.139	1.000	0.086
P5	0.460	-0.320	-0.298	-0.142	0.086	1.000

Table 4: (Continued)

The table shows the estimates of the correlation matrices implied by model (3.3)–(3.4) in the main text for currency portfolios sorted by their characteristics. Parameters are estimated using maximum likelihood assuming normally distributed returns in each regime. The sample of 48 individual currencies runs from November 1983 to September 2011.

CA Regime 1						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.305	-0.240	-0.020	0.003	0.141
P1	-0.305	1.000	-0.208	-0.254	-0.249	-0.265
P2	-0.240	-0.208	1.000	-0.252	-0.247	-0.256
P3	-0.020	-0.254	-0.252	1.000	-0.236	-0.220
P4	0.003	-0.249	-0.247	-0.236	1.000	-0.213
P5	0.141	-0.265	-0.256	-0.220	-0.213	1.000

CA Regime 2						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.321	-0.183	0.309	0.303	0.506
P1	-0.321	1.000	-0.224	-0.345	-0.332	-0.355
P2	-0.183	-0.224	1.000	-0.304	-0.293	-0.288
P3	0.309	-0.345	-0.304	1.000	-0.120	-0.024
P4	0.303	-0.332	-0.293	-0.120	1.000	-0.024
P5	0.506	-0.355	-0.288	-0.024	-0.024	1.000

Value Regime 1						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.198	-0.178	-0.044	0.097	-0.012
P1	-0.198	1.000	-0.228	-0.247	-0.254	-0.250
P2	-0.178	-0.228	1.000	-0.247	-0.252	-0.250
P3	-0.044	-0.247	-0.247	1.000	-0.235	-0.246
P4	0.097	-0.254	-0.252	-0.235	1.000	-0.231
P5	-0.012	-0.250	-0.250	-0.246	-0.231	1.000

Value Regime 2						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	-0.105	-0.054	0.262	0.484	0.328
P1	-0.105	1.000	-0.265	-0.278	-0.260	-0.277
P2	-0.054	-0.265	1.000	-0.264	-0.236	-0.260
P3	0.262	-0.278	-0.264	1.000	-0.070	-0.139
P4	0.484	-0.260	-0.236	-0.070	1.000	-0.032
P5	0.328	-0.277	-0.260	-0.139	-0.032	1.000

HML Regime 1						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	0.117	-0.346	0.215	0.237	-0.239
P1	0.117	1.000	-0.279	-0.184	-0.182	-0.265
P2	-0.346	-0.279	1.000	-0.308	-0.318	-0.220
P3	0.215	-0.184	-0.308	1.000	-0.155	-0.283
P4	0.237	-0.182	-0.318	-0.155	1.000	-0.290
P5	-0.239	-0.265	-0.220	-0.283	-0.290	1.000

HML Regime 2						
	y^w	P1	P2	P3	P4	P5
y^w	1.000	0.516	-0.357	0.674	0.708	-0.129
P1	0.516	1.000	-0.390	0.212	0.235	-0.275
P2	-0.357	-0.390	1.000	-0.417	-0.424	-0.261
P3	0.674	0.212	-0.417	1.000	0.364	-0.266
P4	0.708	0.235	-0.424	0.364	1.000	-0.264
P5	-0.129	-0.275	-0.261	-0.266	-0.264	1.000

Table 5: Portfolio Weights

The table presents optimal mean-variance allocation weights as implied by the estimated mean vectors and covariance matrices of model (3.3)–(3.4) in the main text for currency portfolios sorted by their characteristics. The sample of 48 individual currencies runs from November 1983 to September 2011.

	Carry		
	Regime 1	Regime 2	Unconditional
P1	0.13	0.54	0.18
P2	0.24	0.38	0.25
P3	0.22	0.17	0.21
P4	0.23	0.06	0.21
P5	0.19	-0.15	0.15

	Momentum		
	Regime 1	Regime 2	Unconditional
P1	0.19	0.07	0.17
P2	0.20	0.31	0.22
P3	0.20	0.26	0.21
P4	0.18	0.27	0.19
P5	0.23	0.08	0.21

	Value		
	Regime 1	Regime 2	Unconditional
P1	0.12	0.23	0.13
P2	0.15	0.26	0.16
P3	0.24	0.26	0.24
P4	0.24	0.02	0.21
P5	0.25	0.23	0.25

	IIP		
	Regime 1	Regime 2	Unconditional
P1	0.30	0.72	0.36
P2	0.12	0.24	0.13
P3	0.16	0.12	0.15
P4	0.26	0.01	0.23
P5	0.16	-0.09	0.12

	CA		
	Regime 1	Regime 2	Unconditional
P1	0.22	0.60	0.27
P2	0.14	0.29	0.16
P3	0.24	0.16	0.23
P4	0.19	0.04	0.17
P5	0.20	-0.09	0.16

	HML		
	Regime 1	Regime 2	Unconditional
Carry	0.18	0.04	0.16
Mom	0.10	0.39	0.14
IIP	0.26	0.04	0.23
CA	0.29	0.08	0.26
Value	0.17	0.46	0.20

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