Beyond the Carry Trade: Optimal Currency Portfolios*

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Abstract

We test the relevance of technical and fundamental variables in forming currency portfolios. Carry, momentum and reversal all contribute to portfolio performance, whereas the real exchange rate and the current account do not. The resulting optimal portfolio outperforms the carry trade and other naive benchmarks in an extensive 16 year out-of-sample test. Its returns are not explained by risk and are valuable to diversified investors holding stocks and bonds. Exposure to currencies increases the Sharpe ratio of diversified portfolios by 0.5 on average, while reducing crash risk. We argue that currency returns are an anomaly which is gradually being corrected as hedge fund capital increases.

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1 Introduction

Currency spot rates are nearly unpredictable out of sample (Meese and Rogoff (1983)).[1] Usually, unpredictability is seen as evidence supporting market efficiency, but with currency spot rates it is quite the opposite – it presents a challenge. Since currencies have different interest rates, if the difference in interest rates does not forecast an offsetting depreciation, then investors can borrow the low yielding currencies to invest in the high yielding ones (Fama (1984)). This strategy, known as the carry trade, has performed extremely well and for a long period without any sensible economic explanation. Burnside, Eichenbaum, and Rebelo (2008) show that a well-diversified carry trade attains a Sharpe ratio that is more than double that of the US stock market – itself a famous puzzle (Mehra and Prescott (1985)).

Considerable effort has been devoted to explaining the returns of the carry trade as compensation for risk. Lustig, Roussanov, and Verdelhan (2011a) show that the risk of carry trades across currency pairs is not completely diversifiable, so there is a systematic risk component. They form an empirically motivated risk factor – the return of high-yielding currencies minus low-yielding currencies (HML_{FX})– close in spirit to the stock market factors of Fama and French (1992) and show that it explains the carry premium. But the HML_{FX} is itself a currency strategy, so linking its returns to more fundamental risk sources is an important challenge for research in the currency market.

Some risks of the carry trade are well known. High yielding currencies are known to "go up by the stairs and down by the elevator," implying that the carry trade has substantial crash risk. Carry performs worse when there are liquidity squeezes (Brunnermeier, Nagel, and Pederson (2008)) and increases in foreign exchange volatility (Menkhoff, Sarno, Schmeling, and Schrimpf (2011a)). Its risk exposures are also time-varying, increasing in times of greater uncertainty (Christiansen, Ranaldo, and Söderllind (2010)).

Another possible explanation of the carry premium is that there is some "peso problem" with the carry trade – the negative event that justifies its returns may simply have not occurred yet.[2] Using options to hedge away the "peso risk" reduces

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[1] See also Cheung, Chinn, and Pascual (2005), Rogoff and Stavrakeva (2008), Rogoff (2009)

[2] Barro (2006), Fahri and Gabaix (2007), Gourio, Siemer, and Verdelhan (2011), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011).

abnormal returns, lending some support to this view, but the remaining returns depend crucially on the option strategy used for hedging (Jurek (2009)).

Despite our improved understanding of the risk of the carry trade, the fact remains that conventional risk factors from the stock market (market, value, size, momentum) or consumption growth models, do not explain its returns.[3] Indeed, an investor looking for significant abnormal returns with respect to, say, the Fama-French factors (1992), would do very well by just dropping all equities from the portfolio and investing entirely in a passively managed currency carry portfolio instead.

But there is more to the currency market than just the carry trade. Market practitioners follow other strategies, including value and momentum (Levich and Pojarliev (2011)). The benefits of combining these different approaches became apparent during the height of the financial crisis when events in the currency market assumed historical proportions.[4] Figure 1 shows the performance of three popular Deutsche Bank ETFs that track these strategies with the currencies of the G10. From August 2008 to January 2009, the carry ETF experienced a severe crash of 32.6%, alongside the stock market, commodities and high yield bonds. Even so, this crash was not the "peso event" needed to rationalize its previous returns.[5] But in the same period, the momentum ETF delivered a 29.4% return and the value ETF a 17.8% return. So while the carry trade crashed, a diversified currency strategy fared quite well in this turbulent period.

Coincidently, the literature on alternative currency investments saw major developments since 2008. Menkhoff, Sarno, Schmeling and Schrimpf (2011b) document the properties of currency momentum, Burnside (2011) examines a combination of carry and momentum, Asness, Moskowitz, and Pederson (2009) study a combination of value and momentum in currencies (and other asset classes), and Jordà and Taylor (2009) combine carry, momentum and the real exchange rate.

Most of the studies on alternative currency strategies focus on simple, equal weighted portfolios. The choice of simple portfolios is understandable as there is substantial evidence indicating these typically outperform out-of-sample more

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[3]Burnside, Eichenbaum, and Rebelo (2011), Jordà and Taylor (2011).

[4]Melvin and Taylor (2009) provide a vivid narrative of the major events in the currency market during the crisis.

[5]Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011).

complex optimized portfolios.[6] However, we find that using the historical data up to 2007, an investor would have no reason to want to equal-weight momentum, value and carry. Optimized portfolios are a closer reflection of the uncertainties faced by investors in real time. Namely, they have to deal with the choice of what signals to use, how to weigh each signal, and how to address measurement error and transaction costs.

To study the risk and return of currency strategies in a more realistic setting, we use the parametric portfolio policies approach of Brandt, Santa-Clara, and Valkanov (2009) and test the relevance of different variables in forming currency portfolios.

First, we use a pre-sample test to study which characteristics matter for investment purposes. We test the relevance of the interest rate spread (and its sign), momentum and three proxies for value: reversal, the real exchange rate, and the current account. Including all characteristics simultaneously in the test, allows us to see which are relevant and which are subsumed by others. Then we conduct a comprehensive out-of-sample (OOS) exercise with 16 years of monthly returns. This aims to minimize forward-looking bias – though it does not eliminate it completely.[7]

We find that the interest rate spread, momentum and reversal create economic value for investors whereas fundamentals as the current account and the real exchange rate don't. The strategy combining the relevant signals increases the Sharpe ratio relative to an equal-weighted carry portfolio from 0.57 to 0.86, out-of-sample and after transaction costs. This is a 0.29 gain, about the same as the Sharpe ratio of the stock market in the same period.

Transaction costs matter in currency markets. Taking transaction costs into account in the optimization further increases the Sharpe ratio to 1.06, a total gain of 0.49 over the equal-weighted carry benchmark. The gains in certainty equivalent are even more expressive as the optimal diversified strategy substantially reduces crash risk.

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[6]DeMiguel, Garlappi, and Uppal (2009), Jacobs, Müller, and Weber (2010).

[7]After all, would we be conducting the same out-of-sample exercise in the first place if there were no indications in the literature that momentum and value worked in recent years? Still, unlike naive portfolios, our strategy will not invest in these signals more than justified by the historical data up to that moment in time.

Unlike the typical result in OOS tests of optimized equity portfolios, we find that the optimized portfolio outperforms all naive benchmarks.[8] Also, the risk factors recently proposed to explain carry returns do not explain the returns of the optimized portfolio, which has monthly α's ranging between 1.73 and 2.38 percent. So, while these risk factors may have some success explaining carry returns, they struggle to make sense of our optimal currency strategy.

We assess the benefits of diversification across currency investment strategies for investors already exposed to other asset classes. We find an average increase in the Sharpe ratio of 0.51, a much more impressive gain than the 0.09 increase documented in Kroencke, Schindler, and Schrimpf (2011). Furthermore, including the currency strategies in the portfolio consistently reduces fat tails and left skewness. This contradicts crash-risk explanations for returns in the currency market.

Finally, we regress the returns of the optimal strategy on the level of speculative capital in the market, following Jylhä and Suominen (2011). We find evidence that the returns of the strategy decline as the amount of hedge fund capital increases. This suggests that the returns we document constitute an anomaly that is gradually being arbitraged away by hedge funds.

Our paper is structured as follows. In section 2 we explain the implementation of parametric portfolios of currencies. Section 3 presents the empirical analysis. Section 3.1 describes the data and the variables used in the optimization. Sections 3.2 and 3.3 present the investment performance of the optimal portfolios in and out of sample, respectively. Section 4 compares the performance of the optimal portfolio with naive benchmarks. In Section 5 we test the risk exposures of the optimal portfolio. In Section 6 we assess the value of currency strategies for investors holding stocks and bonds. Section 7 discusses possible explanations for the abnormal returns of the strategy, including insufficient speculative capital early in the sample.

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[8]Brandt, Santa-Clara, and Valkanov (2009) optimized portfolio of stocks also outperforms OOS naive benchmarks.

2 Optimal parametric portfolios of currencies

We optimize currency portfolios from the perspective of an US investor in the forward exchange market. In the forward exchange market, the investor can agree at time t to buy currency i at time $t+1$ for $1/F^i_{t,t+1}$ where $F^i_{t,t+1}$ is the price of one

USD expressed in foreign currency units (FCU). Then at time $t+1$ the investor liquidates the position selling the currency for $1/S^i_{t+1}$, where S^i_{t+1} is the spot price of one USD in FCU. The return (in US dollars) of a long position in currency i in month t is:

$$r^i_{t+1} = \frac{F^i_{t,t+1}}{S^i_{t+1}} - 1 \tag{1}$$

This is a zero-investment strategy as it consists of positions in the forward market only.[9] We use one-month forwards throughout as is standard in the literature.[10] Therefore all returns are monthly and there are no inherited positions from month to month. This also avoids path-dependency when we include transaction costs in the analysis.

We optimize the currency strategies using the parametric portfolio policies approach of Brandt, Santa-Clara, and Valkanov (2009). This method models the weights of assets as a function of their characteristics. The implicit assumption is that the characteristics convey all relevant information about the assets' conditional distribution of returns. The weight on currency i at time t is:

$$w_{i,t} = \theta^T x_{i,t}/N_t \tag{2}$$

where $x_{i,t}$ is a $k \times 1$ vector of currency characteristics, θ is a $k \times 1$ parameter vector to be estimated and N_t is the number of currencies available in the dataset at time t. Dividing by N_t keeps the policy stationary (see Brandt, Santa-Clara, and Valkanov (2009)). We do not place any restriction on the weights, which can

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[9]In reality investors need to post collateral to take positions in forward markets. We ignore that in this study.

[10]Burnside, Eichenbaum, and Rebelo (2008), Burnside (2011), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Menkhoff, Sarno, Schmeling and Schrimpf (2011a,b).

be positive or negative. This reflects the fact that in the forward exchange market there is no obvious non-negativity constraint.

The strategies we examine consist of an investment of 100% in the US risk-free asset, yielding rf_t^{US}, and a long-short portfolio in the forward exchange market. For a given sample, θ uniquely determines a parametric portfolio policy, and the corresponding return each period will be:

$$r_{p,t+1} = rf_t^{US} + \sum_{i=1}^{N_t} w_{i,t} r_{t+1}^i \tag{3}$$

The problem an investor faces is optimizing its objective function picking the best possible θ for the sample:

$$\max_{\theta} E_t \left[U(r_{p,t+1}) \right] \tag{4}$$

We use power utility as the objective function:

$$U(r_p) = \frac{(1 + r_p)^{1-\gamma}}{1 - \gamma} \tag{5}$$

where γ is the coefficient of relative risk aversion (CRRA).[11] The main advantage of this utility function is that it penalizes kurtosis and skewness, as opposed to mean-variance utility, which focuses only on the first two moments of the distribution of returns. So our investor dislikes crash risk and values characteristics that help reduce it, even if these do not add to the Sharpe ratio.

The main restriction imposed on the investor's problem is that θ is kept constant across time. This substantially reduces the chances for in-sample overfitting as only a $k \times 1$ vector of characteristics is estimated. The assumption that θ does not change allows its estimation using the sample counterparts:

$$\hat{\theta} = \arg\max_{\theta} \frac{1}{T} \sum_{t=0}^{T-1} U \left(rf_t^{US} + \sum_{i=1}^{N_t} (\theta^T x_{i,t}/N_t) r_{t+1}^i \right) \tag{6}$$

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[11]Bliss and Panigirtzoglou (2004) estimate γ empirically from risk-aversion implicit in one-month options on the S&P and the FTSE and find a value very close to 4. We adopt this value and keep it thoughout. The most important measures of economic performance of the strategy are scale-invariant (Sharpe ratio, skewness, kurtosis), so the specific choice of CRRA utility is not of crucial importance.

For statistical inference purposes, Brandt, Santa-Clara, and Valkanov (2009) show that we can use either the asymptotic covariance matrix of $\hat{\theta}$ or bootstrap methods.[12]

For the interpretation of results it is important to note that (6) optimizes a utility function and not a measure of the distance between forecasted and realized returns. Therefore, θ can be found relevant for one characteristic even if it conveys no information at all about expected returns. The characteristic may just be a predictor of a currency's contribution to the overall skewness or kurtosis of the portfolio, for example. Conversely, a characteristic may be found irrelevant for investment purposes even if it does help in forecasting returns. Indeed, it may forecast both higher returns and higher risk for a currency, offering a trade-off that is irrelevant for the investor's utility function.

Menkhoff, Sarno, Schmeling, and Schrimpf (2011b) show that momentum strategies incur higher transaction costs than the carry trade. They even find that momentum profits are of little relevance in currencies of developed countries after transaction costs. So one valid concern is whether the gains of combining momentum with carry persist after taking into consideration time and cross-currency variation in transaction costs. Fortunately, parametric portfolio policies can easily incorporate transaction costs that vary across currencies and over time. This is a particularly appealing feature of the method, since transaction costs varied substantially as foreign exchange trading shifted towards electronic crossing networks.

To address this issue we optimize:

$$\hat{\theta} = \arg \max_{\theta} \frac{1}{T} \sum_{t=0}^{T-1} U \left(rf_t^{US} + \sum_{i=1}^{N_t} (\theta^T x_{i,t}/N_t) r_{t+1}^i - \sum_{i=1}^{N_t} \left| \theta^T x_{i,t}/N_t \right| c_{i,t} \right) \quad (7)$$

where $c_{i,t}$ is the transaction cost of currency i at time t, which we calculate as:

$$c_{i,t} = \frac{F_{t,t+1}^{ask} - F_{t,t+1}^{bid}}{F_{t,t+1}^{ask} + F_{t,t+1}^{bid}} \quad (8)$$

This is one half of the bid-ask spread as a percentage of the mid-quote. This

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[12] We use bootstrap methods for standard errors in the empirical part of this paper, as these are slightly more conservative and do not rely on asymptotic results.

assumes the investor buys (sells) a currency in the forward market at the ask (bid) price, and the forward is settled at the next month's spot rate. This may overstate transaction costs. For instance, Mancini, Ranaldo, and Wrampelmeyer (2011) document that effective costs in the spot market are less than half those implied by bid-ask quotes as there is significant within-quote trading.

There is another important point to highlight about transaction costs: for a given month and currency, these are proportional to the absolute weight put on that particular currency. This absolute weight is a function of all the currency characteristics as seen in equation 2, so transaction costs will depend crucially on the time-varying interaction between characteristics. One example is the interaction between momentum and other characteristics. As Grundy and Martin (2001) show for stocks, the way momentum portfolios are built guarantees time-varying interaction with other stock characteristics. For instance, after a bear market, winners tend to be low-beta stocks and the reverse for losers. So the momentum portfolio, long in previous winners and short in previous losers, will have a negative beta. The opposite holds after a bull market. The same applies for currencies, after a period where carry experienced high returns, high yielding currencies tend to have positive momentum. In this case, momentum reinforces the carry signal and results in larger absolute weights and thus higher transaction costs. However, after negative carry returns the opposite happens: high yielding currencies have negative momentum. So momentum partially offsets the carry signal resulting in smaller absolute weights and actually reduces the overall transaction costs of the portfolio. This means the transaction costs of including momentum for an extended period of time in a diversified portfolio policy will be lower than what one finds examining momentum in isolation as in Menkhoff, Sarno, Schmeling, and Schrimpf (2011b).

3   Empirical analysis

As figure 1 shows, combining reversal and momentum with the carry trade considerably mitigated the crash of the carry trade in the last quarter of 2008. Yet this is easy to point out *ex post*. The relevant question is whether investors in the currency market had reasons to believe in the virtue of diversifying their investment

strategy before the 2008 crash. For example, Levich and Pojarliev (2011) examine a sample of currency managers and find that they explored carry, momentum and value strategies before the crisis but shifted substantially across investment styles over time. In particular, right before the height of the financial crisis in the last quarter of 2008, most currency managers were heavily exposed to the carry trade, neutral on momentum and investing *against* value. This raises the question of whether the benefits of diversification were as clear before the crisis as they later became apparent. Equally weighting carry, momentum was not an obvious strategy at the time. This also shows that what appear to be naively simple strategies such as equal weighting carry, momentum, and value are not naive at all and in fact benefit a lot from hindsight.

To address this issue we conduct two tests: i) a pre-sample test with the first 20 years of data up to 1996 to determine which characteristics were relevant back then; ii) an out-of-sample experiment since 1996 in which the investor chooses the weight to put on each signal using only historical information available up to each moment in time.

Section 3.1. explains the data sources and the variables used in our optimization. In section 3.2. we conduct the pre-sample test with the sample from 1976:02 to 1996:02. In section 3.3. we conduct the out-of-sample experiment of portfolio optimization using only the relevant variables identified in the pre-sample test.

3.1 Data

We use data on exchange rates, the forward discount / premium, and the real exchange rate for the Euro zone and 27 member countries of the Organization for Co-operation and Development (OECD). The countries in the sample are: Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, the UK, and the US.

The exchange rate data are from Datastream. They include spot exchange rates at monthly frequency from November 1960 to December 2011 and one-month forward exchange rates from February 1976. As in Burnside, Eichenbaum, Kleshchel-

ski, and Rebelo (2011) we merge two datasets of forward exchange rates (against the USD and the GBP) to have a comprehensive sample of returns in the forward market in the floating exchange rate era.[13]

We calculate the real exchange rates of each currency against the USD using the spot exchange rates and the consumer price index. The Consumer Price Index (CPI) data come from the OECD/Main Economic Indicators (MEI) online database. For the Euro, the series that starts January 1996 was extended back to January 1988 using the weights of the Euro founding members. In the case of Australia, New Zealand, and Ireland (before November 1975) only quarterly data are available. In those cases, the value of the last available period was carried forward to the next month.

We test the economic relevance of carry, momentum, and value proxies combined in a currency market investment strategy. The variables used in the optimization exercise are:

1. **sign**$_{i,t}$: The sign of the forward discount of a currency with respect to the USD. It is 1 if the foreign currency is trading at a discount ($F_{i,t} > S_{i,t}$) and -1 if it trades at a premium. This is the carry trade strategy examined in Burnside, Eichenbaum, and Rebelo (2008), Burnside (2011), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011). Given the extensive study of this strategy we adopt it as the benchmark throughout the paper.

2. **fd**$_{i,t}$: The interest rate spread or the forward discount on the currency. We standardize the forward discount using the cross-section mean and standard deviation across all countries available at time t, μ_{FD_t} and σ_{FD_t} respectively. Specifically, denoting the (unstandardized) forward discount as $FD_{i,t}$, we obtain the standardized discount as: $fd_{i,t} = \frac{FD_{i,t} - \mu_{FD_t}}{\sigma_{FD_t}}$. This cross-sectional standardization measures the forward discount in standard deviations above or below the average across all countries. By construction, a variable standardized in the cross-section will have zero mean, implying that the strategy is neutral in terms of the base currency (the US dollar). Jurek (2009) shows

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[13]The first dataset has data on forward exchange rates (bid and ask quotes) against the GBP from 1976 to 1996 and the second dataset has the same information for quotes against the USD from 1996 to 2011.

that an interest rate spread strategy similar to this outperforms the equally-weighted carry trade based on sign.

3. **mom**$_{i,t}$: For currency momentum we use the cumulative currency appreciation in the last three-month period, cross-sectionally standardized. This variable explores the short-term persistence in currency returns. We use momentum in the previous three months because there is ample evidence for persistence in returns for portfolios with this formation period while there are no significant gains (in fact the momentum effect is often smaller) considering longer formation periods (see Menkhoff, Sarno, Schmeling, and Schrimpf (2011b)). Three-month momentum was also used in Kroencke, Schindler, and Schrimpf (2011). Cross-sectional standardizations means that momentum measures relative performance. Even if all currencies fall relative to the USD those that fall less will have positive momentum.

4. **rev**$_{i,t}$: Long-term reversal is the cumulative real currency depreciation in the previous five years, standardized cross-sectionally. First we calculate the cumulative real depreciation of currency i between the basis period (h) and moment t as an index number $Q_{i,h,t} = \frac{S_{i,t}CPI_{i,h-2}CPI_{t-2}^{US}}{S_{i,h}CPI_{i,t-2}CPI_{h-2}^{US}}$. We use a two-month lag to ensure the CPI is known. We pick $h = t - 60$ which corresponds to 5 years. Then we standardize $Q_{i,h,t}$ cross-sectionally to obtain $rev_{i,t}$. This is essentially the same as the notion of "currency value" used in Asness, Moskowitz, and Pederson (2009). We just use the cumulative deviation from purchasing power parity, instead of the cumulative return as they did, to obtain a longer out-of-sample test period. Reversal is positive for those currencies that experienced the larger real depreciations against the USD in the previous 5 years and negative for the others.

5. **q**$_{i,t}$: The real exchange rate standardized by its historical mean and standard deviation. First, as for reversal, we compute $Q_{i,h_i,t}$ with the difference that here the basis period (h_i) is the first month for which there is CPI and exchange rate data available for currency i. Then we compute $q_{i,t} = \frac{Q_{i,h_i,t}-\overline{Q}_{i,t}}{\sigma_{Q_{i,t}}}$, where $\overline{Q}_{i,t}$ is the historical average $\sum\limits_{j=h_i}^{t} Q_{i,h_i,j}/t$ and $\sigma_{Q_{i,t}}$ is the historical standard deviation $\sigma\left(\{Q_{i,h_i,j}\}_{j=h_i}^{t}\right)$. The real exchange rate is

12

measured in standard deviations above or below the historical average. Jordà and Taylor (2009) also used the de-meaned real exchange rate but our time series standardization ensures only information available up to each moment in time is used. Unlike rev, which is cross-sectionally standardized, q is not neutral in terms of the basis currency (the USD). It will tend to be positive for all currencies when these are undervalued against the USD by historical standards.

6. $\mathbf{ca}_{i,t}$: The current account of the foreign economy as a percentage of Gross Domestic Product (GDP), standardized cross-sectionally. The optimization assumes that the previous year current account information becomes known in April of the current year. The current account data were retrieved from the Annual Macroeconomic database of the European Commission (AMECO), where data are available on a yearly frequency from 1960 onward. Many studies examine the relation between the current account and exchange rates justifying its inclusion as a conditional variable.[14]

In order to be considered for the trading strategies, a currency must satisfy three criteria: i) there must be ten previous years of real exchange rate data; ii) current forward and spot exchange quotes must be available; and iii) the country must be an OECD member in the period considered. After filtering out missing observations, there are a minimum of 13 and a maximum of 21 currencies in the sample. On average there are 16 currencies in the sample.

3.2 Pre-sample results

Table 1 shows the investment performance of the optimized strategies from 1976:02 to 1996:02. We use this pre-sample period to check which variables had strong enough evidence supporting their relevance back in 1996, before starting the out-of-sample experiment.

The two versions of the carry trade ($sign$ and fd) deliver similar performance, with high Sharpe ratios (0.96 and 0.99, respectively) but also with significant

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[14]See, for example, Dornbusch and Fischer (1980), Obstfeld and Rogoff (2005), Gourinchas and Rey (2007).

crash risk (as captured by excess kurtosis and left-skewness). Momentum provides a Sharpe ratio of 0.56, better than the performance of the stock market of 0.40 in the same sample. This confirms the results of Okunev and White (2003), Burnside, Eichenbaum and Rebelo (2011), and Menkhoff, Sarno, Schmeling, and Schrimpf (2011b).

Financial predictors work better in our optimization than fundamentals like the real exchange rate and the current account. Reversal had an interesting Sharpe ratio of 0.36. This confirms the results of Menkhoff, Sarno, Schmeling, and Schrimpf (2011b) and Asness, Moskowitz, and Pederson (2009). The strategies using the current account and the real exchange rate as conditioning variables achieved modest Sharpe ratios (of 0.16 and 0.07), not at all impressive – especially as this is an in-sample optimization.[15]

The seventh row shows the performance of an optimal strategy combining the carry (both $sign$ and fd) with momentum and reversal – all the statistically relevant variables. Already in 1996 there was ample evidence indicating that a strategy combining different variables lead to substantial gains. The Sharpe ratio of the optimal strategy was nearly 40% higher than the benchmark and it produced a 16.43 percentage points gain in annual certainty equivalent.

Adding fundamentals to this strategy does not improve it: the Sharpe ratio increases only 0.01 and the annual certainty equivalent only 13 basis points. An insignificant gain since in-sample any additional variable must always increase utility.

Table 2 shows the statistical significance of the variables, isolated and in combination. The table presents the point-estimates of the coefficients and the bootstrapped p-values (in brackets). We perform the bootstrap by generating 1,000 random samples drawn with replacement from the original sample and with the same number of observations (240 months of returns and respective conditional variables). Then we find the optimal coefficients in each random sample, thereby obtaining theyr distribution across samples.

Taken in isolation, the carry trade variables ($sign$ and fd) and momentum are

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[15]We also tested these variables out-of-sample (although, based on the in-sample evidence, the investor would choose not to consider them) and found that they did not add to the economic value of the strategy.

all significant at the 1% level. Reversal has a p-value of 5.3%.

The current account and the real exchange rate have the wrong sign (under-weighing undervalued currencies and those with strong current accounts) but are not significant. We have known since Meese and Rogoff (1983), currency spot rates are nearly unpredictable by fundamentals. Using time-series methods, Gourinchas and Rey (2007) find that the current account forecasts the spot exchange rate of the US dollar against a basket of currencies.[16] But we find no evidence in the cross section that the current account is relevant for designing a profitable portfolio of currencies. At best, the fundamental information is subsumed by interest rates, momentum and reversal.

Combining all variables confirms our main result. Carry, momentum and reversal are relevant for the optimization, fundamentals are not. The final row shows the results for an optimization using only the variables deemed relevant. The p-values show the four variables contribute significantly to the economic value of the strategy in combination.

Concerning both carry variables ($sign$ and fd), the correlation of their returns was 0.46 from 1976:02 to 1996:02, a value that has not changed much since. So these two ways of implementing the carry trade are not identical and the investor finds it optimal to use both. The $sign$ variable assigns the same weight to a currency yielding 0.1% more than the USD as to another yielding 5% more. In contrast, the fd variable assigns weights proportionally to the magnitude of the interest rate differential. Whenever the USD interest rate is close to the extremes of cross section, the $sign$ is very exposed to variations in its value, while fd is always dollar-neutral.

One word of caution on forward-looking bias is needed here. Our in-sample test shows that in 1996 some of the strategies recently proposed in the literature on currency returns would already be found to have an interesting performance. This is a necessary condition to assess if investors would want to use these variables in real time to build diversified currency portfolios. However, this does not tell us whether there were other investment approaches that would have seemed relevant in 1996 and resulted afterwards in poor economic performance.

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[16]Gourinchas and Rey (2007) derive their result making a different use of the current account information. Namely, they detrend it and also consider net foreign wealth.

3.3 Out-of-sample results

We perform an out-of-sample (OOS) experiment to test the robustness of the optimal portfolio combining carry, momentum, and value strategies. The first optimal parametric portfolio is estimated using the initial 240 months of the sample. Then the model is re-estimated every month, using an expanding window of data, until the end of the sample. The out-of-sample returns thus obtained minimize the problem of look-ahead bias. We do not use q and ca in the optimization as these failed to pass the in-sample test with data until 1996.[17]

The in-sample results also hold out of sample. Table 3 shows that the model using interest rate variables, momentum and reversal achieves a certainty equivalent gain of 10.84 percent over the benchmark, with better kurtosis and skewness. Its Sharpe ratio is 1.15, a gain of 0.45 over the benchmark *sign* portfolio.

Transaction costs can considerably hamper the performance of an investment strategy. For example, Jegadeesh and Titman (1993) provide compelling evidence that there is momentum in stock prices, but Lesmond et al. (2004) find that after taking transaction costs into consideration there are little to no gains to be obtained in exploiting momentum.

Panel B of table 3 shows the OOS performance of the strategies after taking transaction costs into consideration. Clearly transaction costs matter. The Sharpe ratio of the optimal strategy is reduced by 0.29, a magnitude similar to the equity premium, and the certainty equivalent drops from 18.87 percent to just 12.15 percent. Momentum and reversal individually show no profitability at all after transaction costs. This finding mirrors the results of Lesmond et al. (2004) with regard to stock momentum. It also confirms the result in Menkhoff, Sarno, Schmeling, and Schrimpf (2011b) that there are no significant momentum profits in currencies of developed countries after transaction costs.

But we find that transaction costs can be managed. In panel C we adjust the optimization to currency and time-specific transaction costs. We calculate the cost-adjusted interest rate spread variable as: $\widetilde{FD}_{i,t} = sign(FD_{it})(|FD_{it}| - c_{it})$ and standardize it in the cross-section to get $\widetilde{fd}_{it}$. We then model the parametric

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[17]Although including these does not change much the results as they receive little weight in the optimization.

weight function as:

$$w_{i,t} = I(c_{it} < |FD_{it}|) \left[\theta^T x_{i,t}/N_t\right] \tag{9}$$

where $I(.)$ is the indicator function, with a value of one if the condition holds and zero otherwise. We maximize expected utility with this new portfolio policy, estimating θ after consideration of transaction costs.

This method effectively eliminates from the sample currencies with prohibitive transaction costs and reduces the exposure to those that have a high ratio of cost to forward discount. Other, more complex, rules might lead to better results, but we refrain from this pursuit as this simple approach is enough to prove the point that managing transaction costs adds considerable value.

The procedure increases the Sharpe ratio of the diversified strategy from 0.86 to 1.06 and produces a gain in the certainty equivalent of 4.54 percent per year. This gain alone is higher than the momentum or reversal certainty equivalents per se. Indeed, the performance of the diversified strategy with managed transaction costs is very close to the strategy in panel A without transaction costs.

Managing transaction costs is particularly important as these currency strategies are leveraged. Given the high Sharpe ratios attainable by investing in currencies, the optimization picks high levels of leverage. We define leverage as $L_t = \sum_{i=1}^{N_t} |w_{it}|$. This is the absolute value of US dollars risked in the currency strategy per dollar invested in the risk-free asset. The optimal strategy has a mean leverage of 5.94 in the OOS period of 1996:03 to 2011:12. As a result, a small difference in transaction costs can have a large impact in the economic performance of the strategy.

One concern in optimized portfolios is whether in-sample overfitting leads to unstable and erratic coefficients OOS. Figure 2 shows the estimated coefficients of the diversified portfolio with managed costs in the OOS period. The coefficients of the four variables used are very stable, leading to consistent exposure to the conditioning variables.

The optimal diversified portfolio has a robust OOS economic performance. In the next section we compare it with simple strategies proposed in the literature.

17

4 Comparison with naive currency strategies

We want to assess the importance of using our optmization procedure by comparing our strategy with simple alternatives. This is especially important because DeMiguel, Garlappi, and Uppal (2009) show that simple rules of investment have robust out-of-sample performance when compared to optimized portfolios. One could argue though that simple currency strategies are not so naive. The performance of long-short portfolios depends on the characteristic used to sort currencies in the first place. The choice of characteristics to average is thus crucial. Why carry, momentum and reversal and not something else? There is the choice of designing a strategy that is neutral in terms of the basis currency (as fd) or not (as $sign$). The weighing of different currency characteristics is also arbitrary in a naive strategy. So the scope for arbitrary choices influenced by ex post observation of the data is not necessarily small for naive strategies. Still, the simple strategies found in the literature provide a natural benchmark for our optimal portfolio policy.

We compare the economic performance of the optimal diversified strategy with 5 simple portfolios: i) the $sign$ strategy, which is long currencies yielding more than the USD and short the others; ii) the version of momentum (mom_b) proposed in Burnside, Eichenbaum, and Rebelo (2011) which is long currencies with a positive return in the previous month and short the others; iii) an equal-weighted combination of sign and momentum; iv) the interest rate spread strategy (fd); v) an equal-weighted portfolio of the signals used in our portfolio policy – momentum, reversal, $sign$ and fd.

It is questionable whether the EW strategy is a naive approach since this strategy uses the signals selected by the optimized portfolio. But including this EW portfolio allows an assessment of how relevant it is to manage transaction costs and to allow the coefficients in the strategy to differ from equality.

Table 4 shows the economic performance of the optimal strategy compared to the simple alternatives. All strategies include a 100% investment in the risk free asset complemented with a long-short currency portfolio. We scale all simple strategies to have constant leverage throughout the period, set to match the mean leverage of the optimized strategy. This ensures that differences in performance

18

do not depend on differences in leverage. Note that the leverage of the portfolio is optimally chosen indirectly in the maximization of the utility function. The leverage ($L_t = \sum_{i=1}^{N_t} |w_{it}| = \sum_{i=1}^{N_t} |\theta x_{it}|/N_t$) depends both on the estimated coefficients and on the level of the explanatory variables and therefore changes through time. We also include a version of the optimal strategy with constant leverage to assess if time-varying leverage is important to performance.

The optimal strategy, with a Sharpe ratio of 1.06 and a certainty equivalent of 16.69 percent, outperforms all others. The 0.22 gain in Sharpe ratio with respect to the EW strategy (the 'naive' approach that performed the best) is statistically significant with a p-value of 0.027.[18]This is because the optimal coefficients are not equal (as seen in Figure 2) and the simple strategy does not manage transaction costs. The gain in certainty equivalent of 7.13 percentage points is even more expressive.

Perhaps surprising is the unimpressive performance of the combination of $sign$ and mom_b. It achieves a lower Sharpe ratio than the $sign$ strategy alone. This is because leverage is set to a constant level, so the outperformance of this strategy documented in Burnside, Eichenbaum, and Rebelo (2011) comes from time-varying leverage. Whenever a currency yields more than the USD but experiences a negative return in the previous month, the two signals cancel out resulting in a weight of zero for the currency. As a result, the combination of $sign$ and mom_b has time-varying leverage, increasing after months when carry has positive returns and decreasing otherwise.

The optimal strategy with constant leverage has a good performance, with a Sharpe ratio of 0.99, though not as good as the unconstrained strategy. Allowing leverage to change over time leads to lower kurtosis and less negative skewness.

All in all, the evidence on economic performance is clear: the optimal strategy produces a certainty equivalent gain of 7.13 percentage points per year over the best performing naive strategy. This gain is due to a higher Sharpe ratio and lower crash risk (as captured by kurtosis and left-skewness).

In table 5 we regress the excess returns of the optimal strategy on those of the simple portfolios to assess its abnormal returns, captured by the intercept. The

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[18]Computed with same method as DeMiguel, Garlappi, and Uppal (2009).

t-statistics and R-squares are obviously significant, since the optimal strategy is built with similar variables as the naive strategies. But these variables do not fully explain the excess returns which range from 0.68 to 2.28 percent per month. The optimal strategy shows an abnormal return of 8.16 percent per year with respect to the best performing naive strategy.

Figure 3 shows the cumulative excess returns of each naive strategy compared to the optimal diversified portfolio. We also include the excess return on the stock market portfolio for comparison. Currency strategies in general outperform the stock market. The Sharpe ratio of the stock market in the OOS period is 0.29, lower than any currency strategy examined.

But the graph also shows that no simple portfolio systematically outperforms the optimal strategy. This contrasts with the result of DeMiguel, Garlappi, and Uppal (2009) for stocks. This result extends and confirms recent findings that optimization methods can outperform more naive approaches in currency markets (Corte, Sarno, Tsiakas (2009), Berge, Jordà, and Taylor (2010)).

5 Risk exposures

Cochrane (2011) uses the expression "factor zoo" to describe the growing number of risk factors proposed in the literature to explain asset returns. The literature on currency markets is no exception and many sets of risk factors have been proposed, mostly to explain the returns of the carry trade.

Lustig, Roussanov, and Verdelhan (2011a) propose an empirically-motivated high-minus-low factor of currencies sorted on interest rates (HML_{FX}) to explain carry trade returns. This is an approach similar in spirit to the Fama and French (1992) three-factor model for stock returns. Note however that the HML_{FX} factor is itself by construction a carry portfolio. So while this approach establishes that there is systematic risk in the carry trade, it does not provide intuition on what is the fundamental risk source that justifies its returns. Brunnermeier, Nagel, and Pederson (2008) argue that liquidity-risk spirals are the source of risk of the carry trade. They use the innovation in the TED spread and in the VIX as factors proxying for liquidity and risk. Menkhoff, Sarno, Schmeling, and Schrimpf

(2011a) propose innovations in foreign exchange market volatility as a risk factor to explain the carry trade and currency momentum. They also use the innovation in average transaction costs and argue the information in this is subsumed by FX volatility. Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011b) propose consumption growth risk as a factor to explain the carry returns. Table 6 shows the exposure of the optimal diversified strategy (with managed transaction costs) to 8 sets of risk factors.

The first model shows that the currency strategy is not exposed to consumption growth risk.[19] This confirms the results of Burnside (2011) and Jordà and Taylor (2011).

The second and third models show that our strategy is exposed to liquidity risk (as captured by innovations in the TED spread) and increases in stock volatility (as captured by the changes in VIX). The VIX is a more significant variable, its beta has a t-statistic of -3.98 versus -2.90 for the TED spread.

The fourth model regresses the returns of the optimal strategy on innovations in transaction costs (the cross-section average in the forward exchange market). This does not yield significant results as the adjusted R-squared is negative.

The fifth model shows the diversified portfolio, with a t-statistic of -2.15, is exposed to innovations in foreign exchange volatility confirming Menkhoff, Sarno, Schmeling, and Schrimpf (2011a).[20] But the adjusted R-squared is only 1.88, much less than the 7.27 of the VIX.

Our optimal strategy is also somewhat exposed to stock market risk as the CAPM and the Carhart (1997) models show. But the only relevant variable is the excess return on the market portfolio with a t-statistic of 4.02 in the CAPM and 4.08 in the Carhart four-factor model.

The best performing model, in term of adjusted R-squared, is the empirically-motivated HML_{FX} factor of Lustig, Roussanov, and Verdelhan (2011a). In this model we regress the optimal portfolio excess returns on RX (the dollar-return of

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[19]For this we use the monthly growth rate of Real Personal Consumption Expenditures donwloaded from the Federal Reserve of St. Louis.

[20]We follow Menkhoff, Sarno, Schmeling, and Schrimpf (2011a) in computing FX volatility in month t as: $\sigma_{FX,t} = \frac{1}{D_t} \sum_{\tau=1}^{D_t} \sum_{i=1}^{N_\tau} \frac{|r_{i,\tau}|}{N_\tau}$, where D_t is the number of trading days in month t and N_τ is the number of currencies available in day τ.

an equal-weighted average of all currency portfolios) and HML_{FX}, the difference in return between the highest yielding currencies and the lowest yielding currencies.[21] The beta with respect to the HML_{FX} is clearly significant, with a t-stat of 6.54, and the adjusted R-squared of 20.85 is by far the highest among the eight models used.

But the most striking result is the consistently high α of the optimal strategy, ranging between 1.73 and 2.38 percent per month, always significant at conventional levels of confidence. So, while the optimal strategy is exposed to some of the factors proposed in the literature on currency returns, the R-squared is typically low and the abnormal returns highly significant.

There is evidence of time-varying risk exposures in the carry trade (Christiansen, Ranaldo, and Söderllind (2010)). In particular, the exposure of the carry to the stock market rises after shocks to liquidity and risk. This is not captured by the unconditional analysis in table 6. So it is of interest to ask whether the optimal strategy also has time-varying risk.

Following Christiansen, Ranaldo, and Söderllind (2010) we run the following OLS regression:

$$r_{p,t} - rf_t = \alpha + \beta_0 RMRF_t + \beta_1 RMRF_t z_{t-1} + \beta_2 R_{bonds,t} + \beta_3 R_{bonds,t} z_{t-1} + \varepsilon_t \quad (10)$$

where z_{t-1} is a proxy for (lagged) risk and $R_{bonds,t}$ is the excess return of the 10 year US bond over the risk-free rate.[22] As proxies for risk we use the foreign exchange volatility, the TED spread, VIX, the average transaction cost, and leverage. The first four are also used in Christiansen, Ranaldo, and Söderllind (2010). We add leverage as this is time varying in the optimal strategy and could naturally induce time-varying risk.

The results of the regression are in table 7. The only interaction term that is significant is for the TED spread with the market. But the sign of the coefficient is negative, implying the strategy is less exposed to the stock market after a liquidity squeeze. In order for time-varying risk to explain the returns of the diversified strategy, the opposite should happen. All other interaction terms are not

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[21]We retrieve the data from Adrien Verdelhan's webpage. The data is for returns with all currencies and after transaction costs.

[22]Bond returns are from Datastream.

significant, so time-varying risk is of little relevance to explain the performance of the diversified strategy. In particular, there is no evidence that the optimal strategy is riskier when it is more leveraged. In general, the conditional models do not add much to the CAPM, and the large significant α persists after considering time-varying risk.

Either unconditionally or conditionally the risk factors proposed to explain the carry trade can do very little to explain the returns of our optimal diversified currency strategy. This indicates that the optimal strategy exploits market inefficiencies rather than loading on factor risk premiums.

6   Value to diversified investors

We assess whether the currency strategies are relevant for investors already exposed to the major asset classes. Indeed, there is no reason *a priori* that investors should restrict themselves to pure currency strategies, particularly when there are other risk factors that have consistently offered significant premiums as well.

The value of currency strategies to diversified investors holding bonds and stocks is a relatively unexplored topic. Most of the literature on the currency market has focused on currency-specific strategies. One exception is Kroencke, Schindler, and Schrimpf (2011) who find that combining investments in stocks and bonds with currencies improves the Sharpe ratio from 0.34 to 0.43 without entailing an increase in crash risk.

We continue to assume that the investor optimizes power utility with constant relative risk aversion of 4. The returns on wealth are now:

$$R_{p,t+1} = r f_t^{US} + \sum_{j=1}^{M} w_j F_j + \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1} - \sum_{i=1}^{N_t} |w_{i,t}| c_{i,t} \qquad (11)$$

where w_j are the (constant) weights on a set of M investable factors F expressed as excess returns, and $w_{i,t}$ depends on the characteristics and the θ coefficients that maximize utility jointly with w_j.

Table 8 shows the OOS performance of the portfolios with and without the currency strategy. The currency strategy combines the interest rate spread, sign,

momentum, and long-term reversal. Subsequently, each two rows compare a portfolio of investable factors with a portfolio combining these factors with the currency strategy.

The opportunity to invest in currencies is clearly valuable to investors. Including currencies in the portfolio always adds to the Sharpe ratio and raises the certainty equivalent. The OOS gains in certainty equivalent range between 9.99 percentage points for an investment in stocks and bonds and 38.04 percentage points for a diversified investment using the Carhart factors. The gain with respect to the Carhart factors comes mainly from the dismal performance of stock momentum in 2009, when it experienced one of its worst crashes in history (Daniel and Moskowitz (2011), Barroso and Santa-Clara (2012)).

These gains are far more impressive than the gains from adding factors like HML and SMB to the stock market. Indeed, only the inclusion of bonds improves upon the certainty equivalent of the stock market OOS. Generally, the inclusion of SMB, HML, and WML factors improves Sharpe ratios, but this increase is offset by higher drawdowns, resulting in lower certainty equivalents.

Including currencies however leads to substantial gains. This extends the evidence in Burnside (2011) that there is no known set of risk factors that prices currency and stock returns simultaneously. The relevance of the interest rate spread, currency momentum, and long-term reversal to forecast currency returns makes all conventional risk premiums seem small in comparison.

Including currencies in the portfolio of stocks and bonds produces increases in the Sharpe ratio as high as 0.81 for a portfolio of US stocks and currencies. On average adding currency strategies increases the Sharpe ratio by 0.51. This confirms the results of Kroencke, Schindler, and Schrimpf (2011).

One possible justification for the higher Sharpe ratios obtainable by investing in currencies is that these might entail a higher crash risk – as Brunnermeier, Nagel, and Pedersen (2008) shows for the carry trade. But diversified currency strategies do not conform to this explanation. Figure 4 shows how complementing a portfolio policy with investments in the currency market contributes to performance, including kurtosis and skewness. The currency strategies increase Sharpe ratios and certainty equivalents and, most notably, they also reduce substantially the excess kurtosis and left-skewness of diversified portfolios.

24

Our results make it hard to reconcile the economic value of currency investing with the existence of some set of risk factors that drives returns in currencies and other asset classes. The substantial increases in Sharpe ratios combined with the lower crash risk indicate that there is either a specific set of risk factors in the currency market or that currency returns have been anomalous throughout our sample.

7 Speculative capital

We cannot justifiy the profitability of our currency strategy as compensation for risk. The obvious alternative explanation is market inefficieny. This might arise due to insufficient arbitrage capital, possibly because strategies exploring the cross section of currency returns were not well known. Jylhä and Suominen (2011) find carry returns explain hedge fund returns controlling for the other factors proposed by Fung and Hsieh (2004) and that growth in hedge fund speculative capital is driving carry trade profits down.

Following Jylhä and Suominen (2011), we run an OLS regression of the returns of the optimal strategy on hedge fund assets under management scaled by the monetary aggregate M2 of the 11 currencies in their sample ($AUM/M2$) and new fund flows ($\Delta AUM/M2$).[23] The regression uses the out-of-sample returns, after transaction costs, of the optimal strategy from 1996:03 to 2008:12 as the dependent variable. The estimated coefficients (and t-statistics in parenthesis) are:

$$
\begin{array}{ccccc}
r_{p,t} = & 0.08 & -1.47 & (\frac{AUM}{M2})_{t-1} & +3.56 & (\Delta\frac{AUM}{M2})_t \\
& (4.29) & (-3.23) & & (0.36)
\end{array}
$$

The new flow of capital to hedge funds is not significant in the regression but the estimated coefficient has the correct sign. The level of hedge fund capital predicts negatively the returns of the optimal strategy. With a t-statistic of -3.23, this provides convincing evidence that the returns of the diversified currency strategy are an anomaly that is gradually being corrected as more hedge fund capital exploits it.

This opens the question whether the large returns of the strategy are likely

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[23]We thank Matti Suominen for providing us the time series of AUM/M2. See their paper for a more detailed description of the data.

to continue going forward. We note that in the last three years of our sample (2009-2011) the strategy produces a Sharpe ratio of 0.82, lower than its historical average but still an impressive performance (though not much different than the stock market in the same period).

8   Conclusion

Diversified currency investments using the information of momentum, yield differential, and reversal, outperform the carry trade substantially. This outperformance materializes in a higher Sharpe ratio and in less severe drawdowns, as reversal and momentum had large positive returns when the carry trade crashed. The performance of our optimal currency strategy poses a problem to peso explanations of currency returns.

Our optimal currency portfolio picks stable coefficients for the relevant currency characteristics and, by dealing with transaction costs, outperforms naive benchmarks proposed in the literature.

The economic performance of the optimal currency portfolio cannot be explained by risk factors or time-varying risk. This suggests market inefficiency or, at least, that the right risk factors to explain currency momentum and reversal returns have not been identified yet. Investing in currencies significantly improves the performance of diversified portfolios already exposed to stocks and bonds. So currencies either offer exposure to some set of unknown risk factors or have anomalous returns.

The most convincing explanation for the returns of our optimal diversified currency portfolio is that it constitutes an anomaly – one which is being gradually arbitraged away as speculative capital increases in the foreign exchange market.

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Strategy	Max	Min	Mean	std	kurt	skew	SR	CE
fd	15.91	-25.39	19.23	19.47	4.48	-1.23	0.99	18.97
mom	17.31	-11.60	8.01	14.23	1.80	0.21	0.56	11.61
rev	8.38	-11.31	3.09	8.72	2.24	-0.26	0.36	8.95
sign	21.29	-30.11	17.96	18.74	7.35	-0.90	0.96	18.29
ca	2.79	-3.47	0.61	3.86	1.24	-0.44	0.16	7.59
q	2.02	-2.32	0.12	1.79	4.44	-0.74	0.07	7.34
fd, mom, rev, sign	56.83	-32.78	44.30	32.89	5.54	0.66	1.35	34.72
All	60.38	-25.56	45.28	33.70	5.10	0.60	1.34	34.85

Table 1. The in-sample performance of the investment strategies in the period 1976:02 to 1996:02. The optimizations use a power utility with CRRA of 4. The mean, standard deviation and Sharpe ratio are annualized and "Kurt." stands for excess kurtosis.

fd	mom	rev	sign	ca	q
7,93	-	-	-	-	-
[0, 000]	-	-	-	-	-
-	5,10	-	-	-	-
-	[0, 009]	-	-	-	-
-	-	3,46	-	-	-
-	-	[0, 053]	-	-	-
-	-	-	3,71	-	-
-	-	-	[0, 000]	-	-
-	-	-	-	-2,19	-
-	-	-	-	[0, 247]	-
-	-	-	-	-	-0,15
-	-	-	-	-	[0, 648]
4,75	8,10	6,57	2,67	-4,95	-1,08
[0, 051]	[0, 019]	[0, 078]	[0, 085]	[0, 621]	[0, 828]
7,09	7,26	4,37	2,44	-	-
[0, 004]	[0, 006]	[0, 051]	[0, 023]	-	-

Table 2. The statistical significance of the variables in the in-sample period of 1976:02 to 1996:02. The coefficient estimates and bootstrapped p-values (in brackets).

	Max	Min	Mean	std	kurt	skew	SR	CE
Panel A: No transaction costs								
fd	18,64	-29,20	21,38	24,33	2,15	-0,82	0,88	10,89
mom	14,72	-10,03	4,97	13,29	0,57	0,04	0,37	4,39
rev	9,42	-9,67	1,69	9,50	1,42	0,23	0,18	2,84
sign	16,40	-21,21	15,01	21,37	1,95	-0,64	0,70	8,03
all in	26,90	-22,88	38,02	32,98	0,12	-0,14	1,15	18,87
Panel B: With transaction costs								
fd	4,59	-10,92	2,80	7,40	5,01	-1,35	0,38	4,55
mom	0,64	-1,33	-0,02	0,66	17,41	-2,43	-0,03	2,88
rev	0,00	0,00	0,00	0,00	18,62	2,06	0,05	2,91
sign	12,12	-16,30	8,89	15,70	2,14	-0,67	0,57	6,59
all in	20,39	-18,31	19,20	22,20	0,54	-0,16	0,86	12,15
Panel C: With $w_{i,t} = I(c_{it} < |FD_{it}|) \left[\theta^T x_{i,t}/N_t \right]$								
fd	12,83	-20,70	11,91	17,18	2,66	-0,89	0,69	8,35
mom	6,67	-7,01	2,14	6,04	2,37	-0,07	0,35	4,33
rev	3,44	-3,84	-0,37	3,00	4,66	-0,16	-0,12	2,36
sign	18,10	-23,09	12,08	20,23	2,74	-0,76	0,60	5,98
all in	26,70	-22,75	28,48	26,84	0,69	-0,16	1,06	16,69

Table 3. The OOS performance of the investment strategies in the period 1996:03 to 2011:12 with different methods to deal with transaction costs. Panel A presents the results without considering transaction costs. Panel B takes transaction costs into consideration. Panel C excludes all currencies whenever the bid-ask spread is higher than the forward discount, then adjusts the forward discount by the transaction cost. All optimizations use a power utility function with a CRRA of 4 and the coefficients are re-estimated each month using an expanding window of observations in the OOS period of 1996:03 to 2011:12.

Strategy	Max	Min	Mean	std	kurt	skew	SR	CE
$sign$	24.72	-34.04	19.23	32.09	2.06	-0.61	0.60	-2.00
mom_b	63.26	-40.43	14.60	40.69	4.45	0.53	0.36	-17.53
$sign+mom_b$	55.78	-51.58	21.32	45.34	3.31	0.02	0.47	-27.72
fd	20.57	-29.16	17.54	23.77	2.73	-0.64	0.74	7.81
$EW(sign, fd, mom, rev)$	19.69	-25.77	22.76	27.09	1.17	-0.60	0.84	9.56
constant leverage	30.06	-22.39	27.73	27.89	0.92	-0.22	0.99	14.51
Optimal strategy	26.70	-22.75	28.48	26.84	0.69	-0.16	1.06	16.69

Table 4. The performance of naive portfolios in the OOS period compared to the optimal strategy using sign, fd, momentum and reversal. The naive strategies have a constant leverage of 5.94, the same as the optimal strategy on average. The OOS returns are from 1996:03 to 2011:12. The optimization uses an expanding window of returns, re-estimating the coefficients each month. Results with transaction costs.

Strategy	α	t-stat	β	t-stat	R^2
sign	1.39	3.58	0.62	14.92	54.20
mom_b	2.28	4.05	0.08	1.57	1.30
sign+mom_b	1.89	3.74	0.27	7.10	21.17
fd	1.43	3.02	0.65	9.56	32.71
$EW(sign, fd, mom, rev)$	0.68	2.72	0.89	28.85	81.57

Table 5. The OOS performance of the optimal strategy regressed on the naive portfolios. The regressions are standard OLS regressions. The optimal strategy uses sign, fd, momentum and reversal and re-estimates the coefficients in the OOS period every month. Results after transaction costs. The alphas are expressed in percentage points per month. The OOS returns are from 1996:03 to 2011:12.

α	β_1	β_2	β_3	β_4	Adj-Rsquared
		$r_{opt,t} = \alpha + \beta_1 \Delta cons_t + \varepsilon_t$			
2.08	1.31	-	-	-	-0.10
[3.20]	[0.90]	-	-	-	-
		$r_{opt,t} = \alpha + \beta_1 \Delta TED_t + \varepsilon_t$			
2.38	-0.06	-	-	-	3.76
[4.31]	[−2.90]	-	-	-	-
		$r_{opt,t} = \alpha + \beta_1 \Delta VIX_t + \varepsilon_t$			
2.38	-0.46	-	-	-	7.27
[4.41]	[−3.98]	-	-	-	-
		$r_{opt,t} = \alpha + \beta_1 \Delta c_t + \varepsilon_t$			
2.37	26.80	-	-	-	-0.42
[4.21]	[0.45]	-	-	-	-
		$r_{opt,t} = \alpha + \beta_1 \Delta \sigma_{FX.t} + \varepsilon_t$			
2.38	-8.71	-	-	-	1.88
[4.28]	[−2.15]	-	-	-	-
		$r_{opt,t} = \alpha + \beta_1 RMRF_t + \varepsilon_t$			
2.19	0.44	-	-	-	7.43
[4.03]	[4.02]	-	-	-	-
$r_{opt,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_2 + \beta_3 HML_t + \beta_4 WML_t + \varepsilon_t$					
2.07	0.50	0.01	0.20	0.09	6.88
[3.74]	[4.08]	[0.05]	[1.19]	[0.87]	-
		$r_{opt.t} = \alpha + \beta_1 RX_t + \beta_2 HML_{FX.t} + \varepsilon_t$			
1.73	0.32	1.35	-	-	20.85
[3.37]	[1.16]	[6.54]	-	-	-

Table 6. Risk exposures of the optimal strategy. We regress the OOS returns of the optimal strategy (after transaction costs) on each set of risk factors. Standard OLS coefficients (and t-statistics in brackets). The OOS returns are from 1996:03 to 2011:12.

z	α	$RMRF_t$	$RMRF_t z_{t-1}$	$R_{bonds,t}$	$R_{bonds,t} z_{t-1}$	Adj-rsquared
σ_{FX}	2.26	0.46	-0.07	-0.22	0.00	6.70
	[3.95]	[3.73]	$[-0.85]$	$[-0.77]$	[0.01]	-
TED	2.09	0.52	-0.15	-0.04	-0.19	9.31
	[3.69]	[4.33]	$[-2.35]$	$[-0.14]$	$[-1.39]$	-
VIX	2.26	0.52	-0.15	-0.15	-0.07	7.51
	[3.99]	[3.99]	$[-1.60]$	$[-0.53]$	$[-0.51]$	-
c	2.22	0.46	-0.08	-0.18	0.01	6.77
	[3.85]	[3.79]	$[-1.04]$	$[-0.63]$	[0.06]	-
leverage	2.20	0.46	0.15	-0.18	0.04	7.07
	[3.84]	[3.88]	[1.29]	$[-0.71]$	[0.14]	-

Table 7. Time-varying risk of the optimal strategy. In each row we regress the OOS returns, after transaction costs, of the optimal strategy on the market and bond returns, using a different risk proxy as a state variable to account for time-varying risk exposure. We standardize all risk proxies subtracting the mean and dividing by the standard deviation. Standard OLS coefficients and t-statistics (in brackets). The optimal strategy uses sign, fd, momentum and reversal and re-estimates the coefficients in the OOS period every month. The OOS returns are from 1996:03 to 2011:12.

Strategy	Max	Min	Mean	STD	Kurt.	Skew	SR	CE
fd, mom, rev and sign	26,70	-22,75	28,48	26,84	0,69	-0,16	1,06	16,69
Stock market	7,16	-14,94	3,17	12,46	1,36	-0,81	0,25	2,83
Stock market+curr.	27,27	-21,87	27,95	26,93	0,73	-0,16	1,04	16,07
FF factors	19,89	-29,96	12,94	27,41	1,53	-0,84	0,47	-1,53
FF factors+curr.	31,75	-22,26	27,06	25,79	1,32	0,13	1,05	16,83
Carhart factors	33,51	-63,23	20,84	35,67	8,02	-1,37	0,58	-30,46
Carhart factors+curr.	19,29	-24,21	15,78	22,92	0,94	-0,45	0,69	7,58
Stocks and bonds	8,13	-13,74	5,39	12,16	2,15	-0,93	0,44	5,19
Stock and bonds+curr.	23,53	-22,67	27,98	27,47	0,80	-0,28	1,02	15,19

Table 8. The OOS performance of portfolios combining a currency strategy with different background assets. The currency strategy uses momentum, the interest rate spread, reversal and sign. Each row denoted with '+curr.' combines the available factors with the currency strategy. Results with transaction costs. Optimizations carried out with a CRRA of 4 and 240 months in the initial in-sample estimate. The OOS period is from 1996:03 to 2011:12.
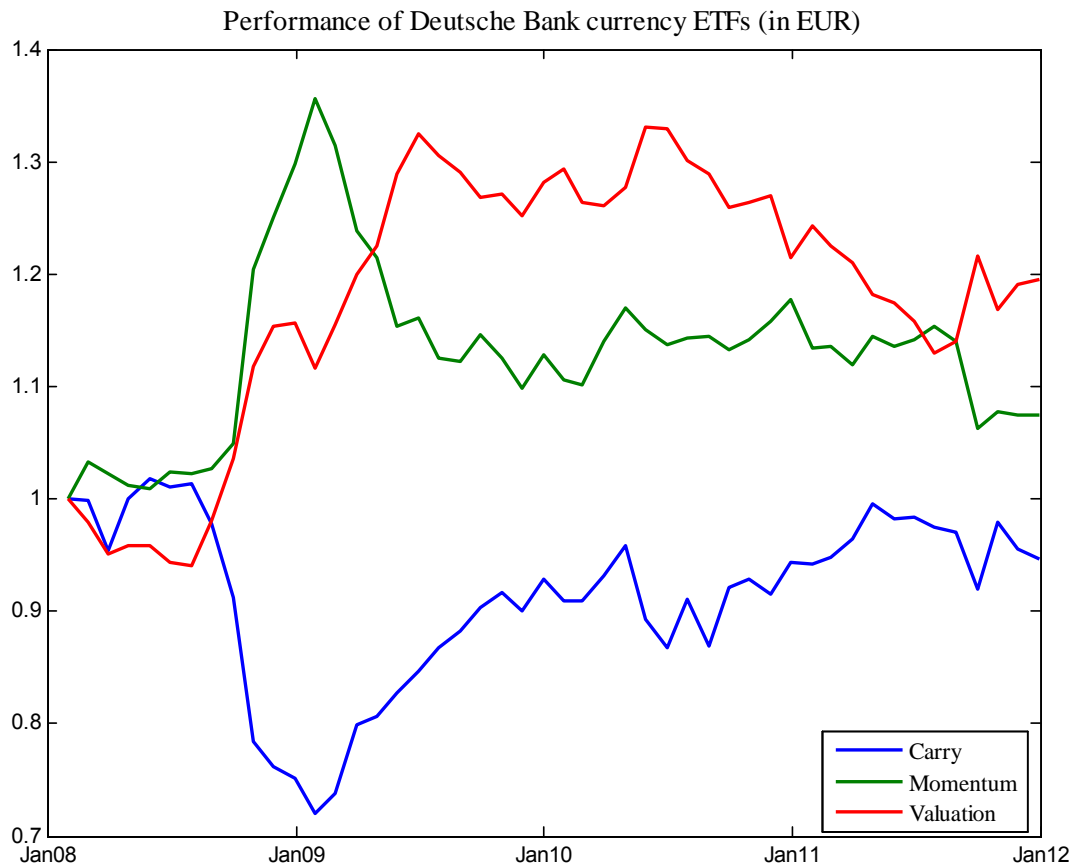
Figure 1. The performance of Deutsche Bank currency ETFs (in euros). Each line plots the cumulative monthly returns of a Deutsche Bank ETF from 2008:01 to 2011:12.
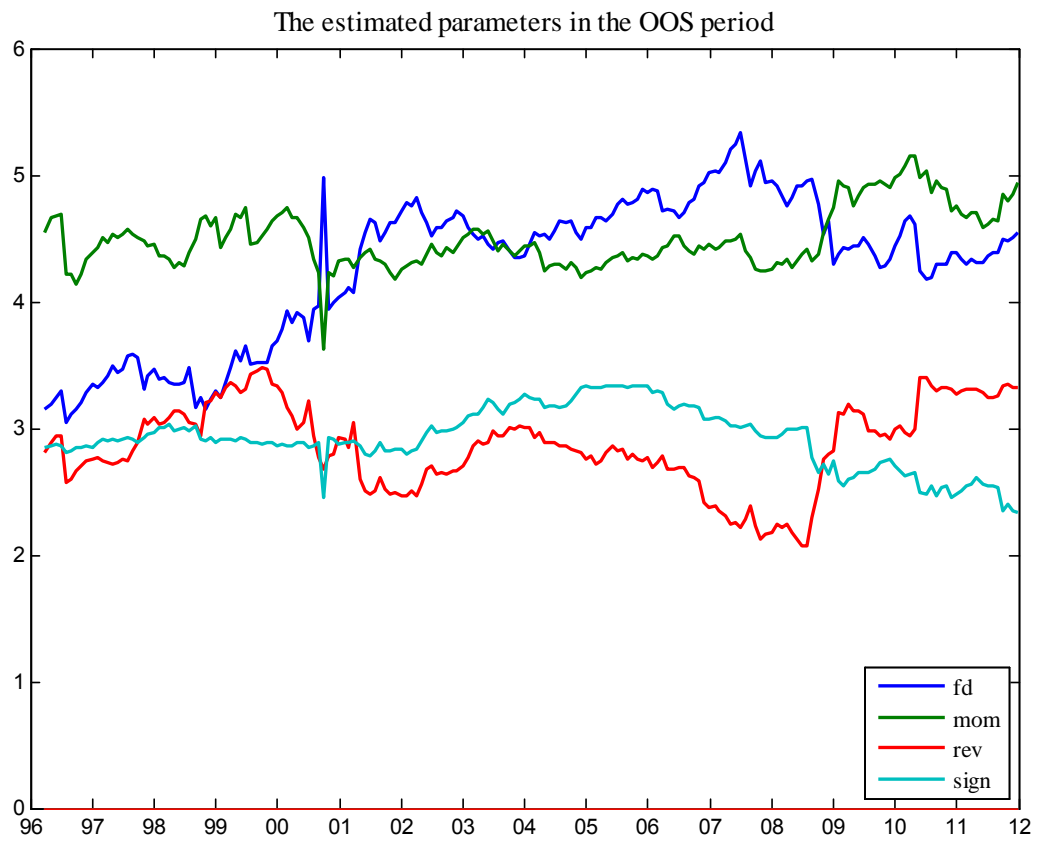
Figure 2. The estimates of the coefficients of the portfolio in the OOS period from 1996:03 to 2011:12. Optimization with CRRA of 4 and considering transaction costs.
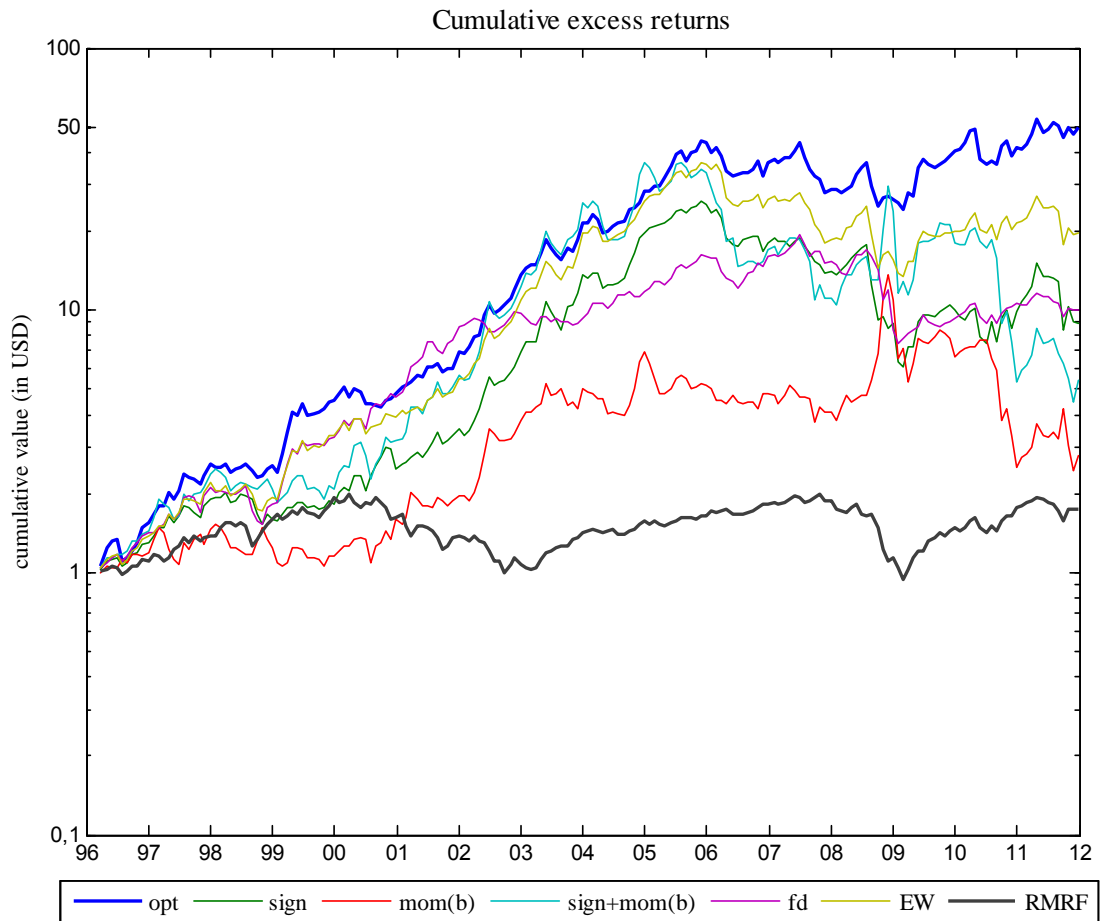
Figure 3. OOS performance of the strategies versus naive portfolios in the period of 1996:03 to 2011:12. The naive currency strategies have a constant leverage of 5.94 to match the mean leverage of the optimized strategy in the OOS period. Returns after transaction costs.
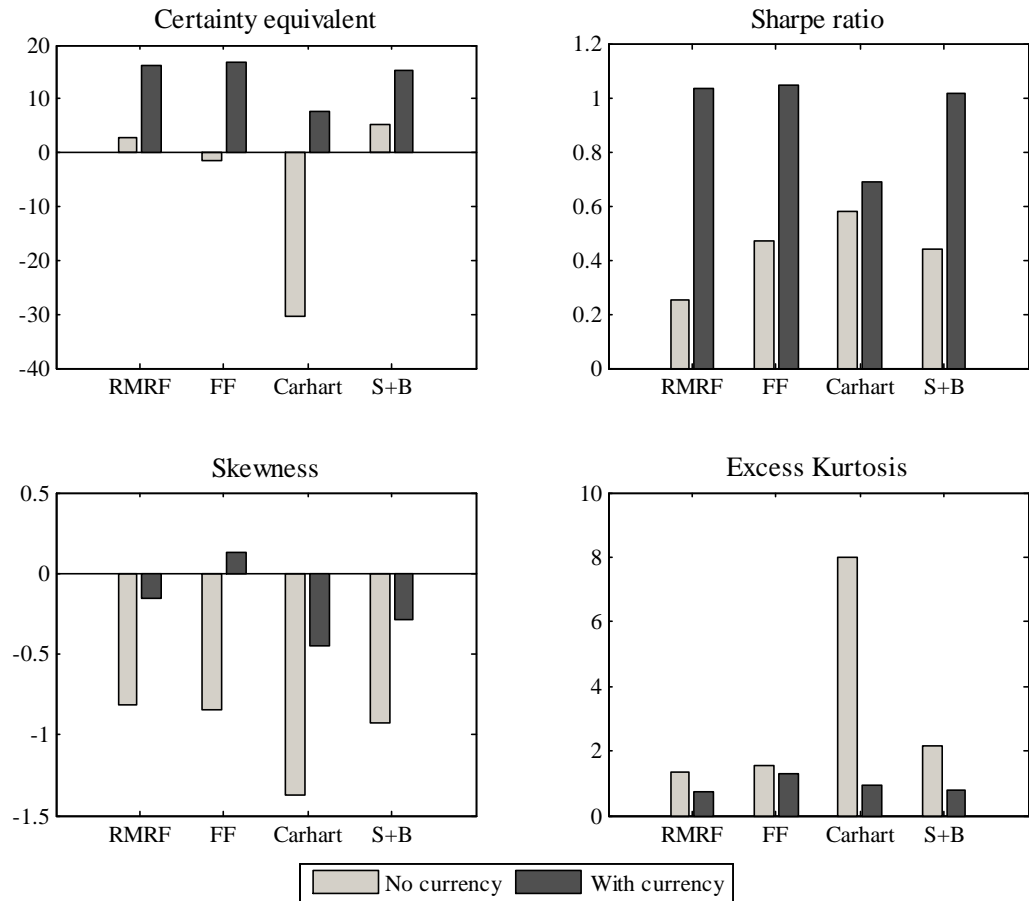
Figure 4. The OOS value of currency strategies for investors exposed to different background risks. Each set of columns shows the performance of an optimized portfolio with the available assets (light grey) and one which combines it with the currency strategy (dark grey). The currency strategy uses the information on the interest rate spread, sign, momentum and reversal. The OOS period is from 1996:03 to 2011:12. Results with transaction costs.