Is currency momentum driven by global economic risk?

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Abstract

This article investigates the potential link between momentum in currency returns and global economic risk as measured by currency return dispersion (RD). We find that the spread on zero-cost currency momentum strategies is larger and highly significant in high RD states compared to low RD states. The results remain robust after using a *t*-statistic cutoff of three as suggested by Harvey et al. (2015). Also, the relation between these momentum payoffs and global economic risk appears to increase linearly in risk. Further tests indicate that the same macroeconomic risk component in currency markets is present in global equity markets. Based on this evidence, we conclude global economic risk as proxied by RD helps to explain currency momentum profits.

Keywords: **r**eturn dispersion, momentum, currency markets, global economic risk

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1. Introduction

The source of the momentum anomaly, as first documented in Jegadeesh and Titman (1993), has sparked intense debate in the academic literature. Explanations for this phenomenon typically fall into one of two categories: mispricing versus risk. After more than two decades of research, resolution of this anomaly remains elusive.[1] Most studies focus on investigating the momentum anomaly in equity markets. A smaller set of studies by Lustig, Roussanov, and Verdelhan (2009), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a, 2012b), and Moskowitz, Ooi, and Pedersen (2012) has documented momentum in currency markets.

Recent studies by Chichernea, Holder, and Petkevich, (2015a, 2015b) have established a link between cross-sectional return dispersion and the accrual anomaly in both stock and bond markets as well as various investment-related anomalies. Following Gomes et al. (2003) and Zhang (2005), they employ cross-sectional return dispersion as a macro state variable that encapsulates general investing conditions faced by firms. Related work by Connolly and Stivers (2003) has found that cross-sectional stock return dispersion appears to be associated with momentum payoffs in equity markets.[2] Another study closely related to ours is Stivers and Sun (2010). The authors employ cross-sectional return dispersion in stock returns as macroeconomic state variable and find that cross-sectional return dispersion in stock returns is negatively related to subsequent momentum premiums. Their results provide strong evidence for that momentum premiums are procyclical. However, no studies have investigated this potential relation in currency markets.

The purpose of this study is to close the literature gap between equity and currency momentum research by investigating the role of cross-sectional return dispersion in currency momentum profits. We begin by testing whether there is a common macro risk underlying both equity and currency markets. For this purpose, we estimate cross-sectional dispersion in global equity markets using a set of domestic country index futures. A principal component analysis is conducted to determine if the variation in cross-sectional dispersion in global equity and currency markets can be explained by a dominant factor. As a robustness check, we test whether

[1] We direct readers to Menkhoff et al. (2012a) for a detailed discussion on this vast literature.
[2] More specifically, they documented momentum in consecutive weekly equity-index returns when the latter week had abnormally high firm-level return dispersion but reversals in consecutive equity-index returns when the latter week had abnormally low dispersion.

dispersion processes in these different markets are cointegrated. Our findings support the existence of a common macro risk factor in equity and currency markets. In this regard, a long-standing puzzle in finance is the weak empirical relationship between stock returns and currency movements.[3] Our results suggest that these two financial markets share a salient common factor, which broadly interpreted reflects macro risk arising from economic uncertainty, market volatility, technological change, and other global forces.[4]

Given that cross-sectional dispersion (RD) is a proxy for macro risk, we investigate the relationship between RD and currency momentum profits. Our data consists of different measures of cross-sectional currency return dispersion (RD) that are sorted into high and low dispersion regimes corresponding to states of economic stress and ease, respectively. This approach is closely related to work by Stambaugh et al. (2012), who investigated the relation between investor sentiment and cross-sectional anomalies in U.S. equity markets. We hypothesize that the momentum payoffs are significantly larger in states of high global economic risk than low economic risk. To test this hypothesis the long and short legs of the currency momentum strategy are regressed on dummy variable models to test whether payoffs depend on the state of the world economy. As a robustness check, we also repeated the analyses using the innovations of a model based on market-adjusted returns of cross-sectional currency dispersion. Our empirical results establish a clear link between cross-sectional currency dispersion and momentum payoffs. Under global economic stress, currency momentum payoffs are considerably larger than in quiet economic times. Moreover, the relation between momentum payoffs and an increase in global risk appears to be linear, which is supported by various robustness checks. By providing a risk-based explanation for the momentum phenomenon in currency markets, we extend equity market research by Connolly and Stivers (2003) and Stivers and Sun (2010). Surprisingly, our results provide strong evidence that momentum payoffs in currency markets are countercyclical. This interesting result, contrary to Stivers and Sun (2010) who document that momentum payoffs in the stock market are procyclical, needs to investigated further in future research.

[3] For literature reviews of the stock-return/exchange-rate puzzle, see Karolyi and Stulz (2003) and Armstrong, Knif, Kolari, and Pynnönen (2102).

[4] These findings complement Grobys' (2015) recent finding that the volatilities of equity and currency markets are driven by a common factor in times of economic stress.

Our paper is organized as follows: Section 2 presents a brief overview of the literature related to the momentum anomaly in currency markets. Section 3 describes the data. Section 4 presents the methods and results. Section 5 concludes.

2. Literature Review

Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) have observed that foreign exchange (FX) markets are more liquid than equity markets and feature considerable transaction volumes with relatively low transaction costs. Additionally, they are populated largely by sophisticated professional investors, and there are no natural short-selling constraints that prevent the shorting of past loser assets to implement momentum strategies. Consequently, FX markets lower the hurdle for generating significant excess returns from momentum strategies.

Surprisingly, only scant attention has been paid to exploring momentum strategies in the cross section of currency returns. Earlier literature has generally focused on momentum strategies in the time series of currencies -- that is, momentum strategies where individual currencies are traded depending on various signals such as moving average cross-overs, filter rules, channel breakouts, and so on (e.g., see Okunev and White (2003)). The profitability of these strategies has been shown to be short lived as more traders learn to exploit them. An excellent summary of this literature is provided by Menkhoff and Taylor (2007).

Asness, Moskowitz, and Pedersen (2013) reported profitable momentum strategies across different asset classes and geographical markets. Relevant to currency momentum, they focused on the G-10 currencies and used cumulative past 12-month currency returns (skipping the most recent month) in the formation period to implement currency momentum strategies. By contrast, Lustig et al. (2009), Burnside et al. (2011), Menkhoff et al. (2012a, 2012b), and Moskowitz et al. (2012) employed a one-month formation period and a subsequent one-month holding period when implementing momentum-based trading strategies in currency markets. We hereafter refer to this strategy as *MOM* (1,1). For example, Menkhoff et al. (2012a) used a sample period from January 1976 to January 2010 for analyzing momentum strategies for 48 currencies. Their study employed one-month forward and spot data to implement momentum strategies. The evidence indicated that, irrespective of the formation period (e.g., 1, 6 and 12 months), the payoffs on currency momentum strategies are the largest for a 1-month holding period. The best 1-month performer in terms of both excess returns and Sharpe ratios had a 1-month formation period, which we hereafter denote *MOM* (1,1). Furthermore, they found that the momentum payoffs are mainly driven by spot moves. Even though high-momentum currencies tended to have higher interest rates than other currencies, momentum strategies implemented in currency markets and carry strategies are quite different. Lustig et al. (2011) and Menkhoff et al. (2012a) documented that the return correlations between the spreads of these two strategies are small and sometimes even negative.

Similarly, Burnside et al. (2011) used 20 major currencies over the sample period 1976-2010 to implement *MOM* (1,1). Their results showed that the equally-weighted *MOM* (1,1) strategy appears to be highly profitable, yielding an average payoff of 4.5 percent per annum with a standard deviation of 7.3 percent and Sharpe ratio of 0.62. The strategy's payoffs are found to be slightly positively skewed as in Menkhoff et al.'s (2012a) study.

Following previous currency momentum literature, we utilize the *MOM* (1,1) strategy to test our research hypothesis that momentum profits in currency markets are associated with global economic risk.

3. Data

Different measures for compounding cross-sectional stock return dispersion (RD) have been employed in equity market studies. For example, Maio (2013) and Stivers and Sun (2010) utilized equity stock portfolios for their calculations. Maio (2013, p. 4) argued that the advantage of using portfolios in the computation of RD instead of using the whole cross section of individual stocks is that noise associated with illiquid or small stocks and other extreme outliers is mitigated. Alternatively, Chichernea et al. (2015a) and Jiang (2010) used individual stocks listed on the NYSE and AMEX and excluded the stocks in the lowest size decile. In this regard, Chichernea et al. (2015a) commented that a measure based on the full universe of individual stocks is more informative of the cross section of stock returns.

Since there is as yet no consensus on which type of measure is most appropriate to compound RD, we computed three different methods to estimate cross-sectional RD in currency returns. Our first measure employs portfolios. We downloaded data for six currency portfolios sorted by local interest rates from Hanno Lustig's webpage and compounded the cross-sectional currency RD as follows:

$$RD_{1t} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_{i,t}^{Carry} - \overline{R_{\iota,t}^{Carry}}\right)^2}, \tag{1}$$

where $R_{i,t}^{Carry}$ is the excess return of portfolio *i* sorted by local interest rates at time *t*, and *N* = 6.[5] Our second measure makes use of individual currencies. In computing this measure we followed Chichernea et al. (2015a) and Jiang (2010) and downloaded a set of 39 individual currencies from Adrien Verdelhan's website. Subsequently, we compounded the second measure for cross-sectional currency RD as follows:

$$RD_{2t} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(R_{j,t}^{Spot} - \overline{R_{J,t}^{Spot}}\right)^2}, \tag{2}$$

where $R_{j,t}^{Spot}$is the sport exchange rate of currency *j* at time *t*, and *M* = 39.[6] The third, and last, measure is based on portfolios sorted by momentum. We used the same data for the 1-month formation and 1-month holding periods as in Menkhoff et al. (2012) and computed this measure as follows:

$$RD_{3t} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left(R_{k,t}^{Momentum} - \overline{R_{k,t}^{Momentum}}\right)^2}, \tag{3}$$

where $R_{k,t}^{Momentum}$ is the excess return of portfolio *k* (sorted by their past month returns) at time *t*, and *K* = 6.[7] We match the monthly data sets with each other over the sample period February 1984 to January 2010. Figure 1 plots the three-month moving averages of our different measures as well as the corresponding first principal component. Visual inspection shows that they closely follow similar time series paths. In Figure 2 we plot the three-month moving average time series of currency return dispersion RD_{2t} employing all available currencies.[8] To investigate the relation between the cross-sectional dispersion in currencies and economic events that had severe impacts on the

[5] A detailed description of how the portfolios of currency excess returns sorted by local interest rates are computed is provided in Lustig et al. (2011). The data are downloaded at http://web.mit.edu/adrienv/www/Data.html.
[6] The data are available at http://web.mit.edu/adrienv/www/Data.html.
[7] The dataset used in Menkhoff et al.'s (2012) paper is downloaded from the data library of the *Journal of Financial Economics*, see http://jfe.rochester.edu/data.htm.
[8] Our empirical findings (unreported) are virtually the same when using RD_{1t} orRD_{3t}.

global economy, we also highlight the 10% of observations, where the level of RD is the highest. A visual analysis of Figure 2 shows clearly that the peaks in the time series of cross-sectional RD in currencies coincide with major economic events that had a considerable impact on the world economy. For instance, the last peak in the time series of our cross-sectional RD measure occurred in the wake of the bankruptcy of Lehman Brothers which marked the beginning of the worldwide financial crises. The observations from October 2008 to March 2009 fell in to 10% of observations, where our cross-sectional RD measure was the highest. This period is well-known as the worldwide financial crisis period. Furthermore, the first peak coincides with the well-known oil-price collapse because in the first half of 1986 crude oil prices fell to about $12 a barrel, back to their level of 1974. Similar arguments hold for the other economic events that happened to have an impact on the global economy. Our analysis of Figure 2 provides strong evidence that periods of high RD indeed capture times of economic stress that are not exclusively related to market-specific events associated with the currency market itself.

Next, we estimate market-adjusted versions of RD denoted as relative return to dispersion (RRD) as follows:

$$RRD_{1t} = \alpha_1 + \beta_1 \left(\frac{1}{N}\sum_{i=1}^{N} R_{i,t}^{Carry}\right) + \gamma_1 \left|\frac{1}{N}\sum_{i=1}^{N} R_{i,t}^{Carry}\right| + \varepsilon_{1t}, \tag{4}$$

$$RRD_{2t} = \alpha_2 + \beta_2 \left(\frac{1}{M}\sum_{j=1}^{M} R_{J,t}^{Spot}\right) + \gamma_2 \left|\frac{1}{M}\sum_{j=1}^{M} R_{j,t}^{Spot}\right| + \varepsilon_{2t}, \tag{5}$$

$$RRD_{3t} = \alpha_3 + \beta_3 \left(\frac{1}{K}\sum_{k=1}^{K} R_{k,t}^{Momentum}\right) + \gamma_3 \left|\frac{1}{K}\sum_{k=1}^{K} R_{k,t}^{Momentum}\right| + \varepsilon_{3t}. \tag{6}$$

These RRD measures are similar to those in Chichernea et al. (2015a), who observed that RRD is orthogonal to both ordinary and absolute market returns.

To estimate the cross-sectional return dispersion of global equity markets, we use 21 different domestic stock indices.[9] The same sample of stock indices has been used in Grobys' (2014) study who investigates the global momentum payoffs in times of recessions. Returns for these stock indices are compounded in their home currencies. By using their local currencies rather than the US-dollar converted indices ensures that any potential effect cannot be driven by

[9] Table 1 in Grobys (2014) presents an overview of the domestic stock indices employed.

the dollar-factor. Each stock index represents a well-diversified basket of large stocks. Using these data series, cross-sectional global equity market dispersion is computed as:

$$RD_t^{Equity} = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(R_{l,t}^{Equity} - \overline{R_{l,t}^{Equity}}\right)^2}, \qquad (7)$$

where $R_{l,t}^{Equity}$ is the return of stock index l at time t, and L = 21. We also computed the corresponding market-adjusted versions of RD denoted as relative return to dispersion (RRD) as:

$$RD_t^{Equity} = \alpha_4 + \beta_4\left(\frac{1}{L}\sum_{l=1}^{L} R_{l,t}^{Equity}\right) + \gamma_4\left|\frac{1}{L}\sum_{k=1}^{K} R_{l,t}^{Equity}\right| + \varepsilon_{4t}. \qquad (8)$$

The data series for currency and equity markets are matched so that RD_t^{Equity} runs from April 1994 to January 2010.

Finally, we use the same data for the momentum strategy based on a 1-month formation and 1-month holding period as in Menkhoff et al. (2012a). The first currency portfolio consists of currencies with the lowest returns in the previous month before portfolio formation, whereas the sixth currency portfolio consists of currencies with the highest past month returns. The long-short strategy is long portfolio 6 and short portfolio 1. Summary statistics for our sample data are reported in Table 1.

4. Empirical Results

4.1 Does currency return dispersion measure global economic risk?

Chichernea et al. (2015a) have conjectured that "… RD is likely to capture the uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring." (2015a, p. 147) They cited earlier work by Pastor and Veronesi (2009) on new technology innovations becoming a systematic risk affecting stock price. Stivers and Sun (2010) argue that "… RD may contain incremental information about the current state of the economy, beyond market-level return." (2010, p.988) They cited earlier work from Stivers (2003) and Loungani et al. (1990) that supports the notion that RD may serve as a state variable. "Stivers notes that RD is higher during economic recessions and finds that RD has incremental information about subsequent market volatility. Loungangi et al. find that RD tends to lead unemployment, which suggests a link between RD and economic reallocation across firms." (2010, p.989) Extending this logic to the present context, we propose that cross-sectional volatile currency patterns in world currency markets arise from time-varying uncertainty about future global economic conditions. Bringing together these two strands of literature, and taking into account the results of our empirical analysis presented in the previous section, we hypothesize that, if currency return dispersion captures global economic risk, the same risk component should be present in global equity markets also. To empirically test this hypothesis, we first conduct a principal component analysis of the three-months moving averages of RD_{2t} and RD_t^{Equity}, which are assumed for the moment to be stationary time series.[10] Figure 2 plots these variables over time as well as the time series of the first principal component. A visual inspection of both these time series in Figure 3 reveals similar trending behavior, which is also reflected in the first principal component. The eigenvalue of the first principal component of the covariance matrix has a magnitude of 1.50, which is about three times larger than the eigenvalue of the second principal component. In this respect, the first principal component explains 75 percent of the variation. We interpret this evidence to mean that there is one dominant component present in both time series. We also computed the eigenvalues for the three-month moving averages of the market-adjusted versions, RRD_{2t} and RRD_t^{Equity}. Confirming our previous finding, the first principal component of the covariance matrix explains 73 percent of the variation.[11]

Employing principal component analysis requires stationarity of the time series analyzed. Assuming for the moment that this condition holds, we tested the order of integration for the smaller sample period from April 1994 to January 2010 using the augmented Dickey-Fuller test (ADF) for the three-month moving averages $RD_{t,13}^{Currency}$ and RD_t^{Equity}. The results in appendix Table A.2 indicate that the time series do *not* exhibit stationarity on a common 5% level for the shorter sample period. If our hypothesis that the currency and equity market would incorporate a common risk is true, and both time series are integrated, we would expect their time series to share a common stochastic trend. As a test, we estimate the residuals $\hat{u}_t$ of the following cointegration regression equation:

[10] See Table A.1 in the appendix.
[11] The corresponding vector of eigenvalues is (1.46, 0.54).

$$RD_{t,13}^{Currency}=\delta \cdot RD_{t,13}^{Equity} + u_t, \tag{9}$$

where $RD_{t,13}^{Currency}$ is the three-month moving average of RD_{2t} (see Figures 1 and 2), and $RD_{t,13}^{Equity}$ is the three-month moving average of RD_t^{Equity}. The estimated residuals $\hat{u}_t$ are plotted in Figure 4. As shown there, the residuals do not exhibit patterns of a linear trend even though there is no intercept in the cointegration regression. Next, we conduct ADF tests for cointegration. The first test statistic does not account for deterministic terms, whereas the second one accounts for an intercept term. The estimated test statistics are -3.72 and -4.12, respectively. The critical values for these tests are different from the ordinary ADF test. Since the 1 percent significance level for the first (second) test statistic is -3.39 (-3.96), the tests indicate stationarity of $\hat{u}_t$ at any significance level. This evidence indicates that $RD_{t,13}^{Currency}$ and $RD_{t,13}^{Equity}$ are linked together in the long-term. In turn, their cointegrated relationship implies that the same macroeconomic risk component is present in both currency and equity markets.[12] The purpose of our cointegration analysis is not to suggest that the currency market captures the global economic risk that is being transferred to the equity markets or vice versa. However, our findings provide strong evidence for that first, the cross-sectional return dispersion in the currency markets caches global economic risk, and second, this risk component is simultaneously cached in cross-sectional dispersion in global equity markets also. Future research may investigate which asset market or asset class, if any, may be the core driver of this phenomenon. In what follows, we make use of our previous findings and explore whether the information about economic states cached in the cross-sectional return dispersion in currencies can help to explain the payoffs of currency momentum returns.

4.2 Currency return dispersion and momentum returns

In contrast to Stivers and Sun (2010), who essentially regress the payoff of an equity momentum series over holding period months *t* to *t*+5, we choose the design our empirical tests of currency RD and momentum in the spirit of Stambaugh et al. (2012), who investigated the association between investor sentiment and various cross-sectional asset pricing anomalies in the

[12] The parameter estimate $\hat{\delta}$ of equation (8) is 0.45 with *t*-statistic of 33.31. The R-squared of the regression is 0.14. If cointegration holds, the parameter estimate is super-consistent. We also run the regression with lagged values of RD_t^{Equity}, or $RD_{t,13}^{Currency}=\delta \cdot RD_{t,13}^{Equity} + u_t$, and tested the residuals again. The results did not change.

U.S. stock market.[13] The authors divided time series observations on market sentiment into above and below median values corresponding to high and low investor sentiment, respectively. Since from our point of view Stambaugh et al.'s (2012) approach is most accurate to meet our research question, we follow this setup and divide intertemporal observations on cross-sectional currency return dispersion into above and below median values indicating high and low RD, respectively.

As mentioned above, we classify each month as following either a high or low dispersion month. As in Chichernea et al. (2015a) and Stivers and Sun (2010), we utilize a three-month moving average of RD measures in equations (1) to (3). High (low) dispersion months have three-month RD values above (below) their respective sample median. Average returns are compounded separately for the high and low dispersion months. Table 2 reports the results for the currency excess returns for our three measures of RD plus the first principal component.[14]

The results in Table 2 indicate that the spreads of the zero-cost momentum strategy are significantly larger in high compared to low RD states. Depending on the RD measure, spreads vary between 1.17 percent and 1.43 percent per month in high RD states with corresponding Newey-West (1987) *t*-statistics between 3.90 and 4.62 significant at any level. Our results remain robust after using a *t*-statistic cutoff of three as suggested by Harvey et al. (2015). In low RD states, spreads are considerably lower and vary between 0.31 percent and 0.55 percent per month. A principal component analysis suggests that the three-month moving average of the three time series RD_1, RD_2 and RD_3 exhibit one dominant eigenvalue of 2.47.[15] The first principal component explains 82 percent of the variation in our three measures, which suggests that there is a common underlying risk. Table 2 shows that, when we employ the first principal component of the three RD measures, the difference between high and low states' average RD has an economic magnitude of 1.04 percent per month with a Newey-West (1987) *t*-statistic of 3.11. Again, this result is robust when taking into account the *t*-statistic cutoff as suggested by Harvey et al. (2015). Chichernea et al. (2015a) who investigate if RD explains the accrual and

[13] Another concern with respect to Stivers and Sun's (2010) empirical approach is that they do not control for past formation period returns. More precisely, a higher spread in the formation period might lead to higher momentum payoffs in the holding period. That is, cross-sectional RD could simply pick up the dispersion in formation period returns.

[14] Employing a principal component analysis requires that the time-series are stationary. In Table A.1 in the appendix, we report the results for ADF tests. The tests reveal that the three-month moving averages of our three different measures for currency return dispersion are stationary at a 1% significance level.

[15] The vector of eigenvalues is (2.47, 0.35, 0.18).

investment anomalies find that “the accrual premium is almost five times higher during states with high RD. The investment premium produces 1.37% per month during high return dispersion states and essentially zero if return dispersion is low.” (2015a, p.2). Moreover they conclude: “We argue that our results support a risk-based interpretation for the accrual and investment anomalies.” (2015a, p.15). Analogously, interpreting states of high cross-sectional dispersion in currency returns as a proxy for high global economic risk, the results strongly support a risk-based explanation for the existence of momentum profits in currency markets. Interestingly, this result is contrary to the corresponding findings for an equity market context, as documented in Stivers and Sun (2010), who conclude, that equity market momentum is procyclical. A possible explanation for this phenomenon is that the common currency momentum and the traditional equity momentum strategies are quite different from each other even though both are labelled as momentum strategies. While the commonly used currency momentum strategy sorts currencies by the previous month return, traditional equity market momentum strategies sort stocks based on the cumulative 6 to 12 months prior returns skipping the previous month. It is likely that these different sorting approaches capture quite different asset features. We encourage future research to explore this phenomenon is more detail.

Lustig et al. (2011) proposed a two-factor asset pricing model consisting of dollar risk and carry risk factors. The dollar risk factor corresponds to the equal-weighted average of currency returns, whereas the carry risk factor is a zero-cost strategy that is long in a portfolio of currencies with high interest rates and short in a portfolio of currencies with low interest rates. The authors show that these two risk factors are highly correlated with the first and second principal components explaining about 82 percent of the cross-sectional variation in currency returns.[16] To check the robustness of our results, we include these two risk factors in our regression model and repeat the previous analysis. After risk-adjustment, the results in Table 3 are virtually the same as in Table 2. The difference between the risk-adjusted *MOM* (1,1) spread in bad versus good states of the global economy is still 1.00 percent per month (significant at any level).

As an additional robustness check, we repeat the analysis using three-month moving averages of three different measures for relative currency return dispersion in equations (4) to

[16] In Table 2 Lustig et al. (2011) shows that the first two principal components explain even 87 percent in developed countries.

(6). We also include the first principal component in our analysis. Table 4 contains the results, which do not change our earlier inferences.

Next, we examine the relationship between RD and expected currency returns in more detail. Here we follow Chichernea et al. (2015a) by dividing periods into four different states of the world as in Petkova and Zhang (2005): *state 1* (good state) corresponds to the 10 percent of lowest observations for RD, *state 2* corresponds to below-average RD, excluding the 10 percent lowest observations, *state 3* corresponds to above-average RD excluding the highest 10 percent observations; and *state 4* (bad state) corresponds to the 10 percent of highest observations for RD. As before, when determining the states of the global economy, we utilize three-month moving average representations of RD and computed average returns. The analyses incorporate all three measures of RD as well as the first principal component. Results are reported in Table 5. Momentum payoffs are higher in states 3 and 4 of the global economy than in states 1 and 2. Using the three-month moving average of RD_2 as a sorting variable, the spread is linear and strictly increasing as we move from state 1 to state 4. The linearity of payoffs is consistent with a risk-based explanation as payoffs increase as risk in the global economy rises.

To further check robustness, we use relative currency return dispersion measures in equations (4) to (6). Again, three-month moving averages of our RRD measures are used and the previous analysis is repeated. The results in Table 6 do not change our earlier inferences.

Another concern that could be raised is that the RD effect is mechanical in nature.[17] For example, a higher spread in the formation period might lead to higher momentum payoffs in the holding period. That is, our cross-sectional RD measures could simply pick up the dispersion in formation period returns. In appendix Figure A.1, we plot the time series of the three-month moving averages of the first principal component (of three different measures of currency return dispersion) and the spread between winner and loser portfolios in the formation period. The correlation is 0.68. To control for dispersion in formation period returns, for risk-adjustment purposes, we include in the regression model the spread between winner and loser portfolios in the formation period and repeat the previous analysis. To run this analysis, we employ the same data as in Verdelhan (2012) (i.e., downloaded from Adrien Verdelhan's website data library). The data set contains 39 currency spot USD-crosses with the sample period from 1983:11 to 2010:1. Panel B of Table 1 gives details of this data set. We compound momentum returns as in

[17] We thank Peter Nyberg for encouraging us to take this issue into account.

Menkfoff el al. (2012a, Section 3). Appendix Table A.3 gives descriptive statistics for these different samples. Even though our spread is 0.11 percent per month lower than the momentum spread reported in Menkhoff et al., the portfolios exhibit very similar properties.

We also compound the dollar and carry factors as in Lustig et al. (2011). Appendix Table A.4 compares these risk factors with the data sets used in Menkhoff et al. (2012a) and Lustig et al. (2011). Table A.4 shows that the risk factors are very similar to those reported in previous literature. Next, to adjust for risk, we include the spread between the past returns of the winner and loser portfolios of our *MOM* (1,1) strategy in the regression model. The loading on the spread of past returns is significantly negative and increases the magnitude of the spread.[18] Controlling for dispersion in formation period returns, we repeat the previous analysis and test whether return differences between high and low dispersion states are significantly larger than zero. The results in appendix Table A.5 again support our previous findings.

5. Conclusion

Numerous studies have attempted to detect a relationship between equity returns and currency movements but have found either no significant evidence or weaker evidence than predicted by theory. We found that cross-sectional currency return dispersion (RD) and cross-sectional global equity RD are cointegrated. As such, returns in currency and equity markets are driven by the same underlying component, broadly interpreted here as global economic risk. Given RD proxies macro risk, we subsequently sought to establish a link between currency momentum profits and currency RD. Several measures of cross-sectional currency RD, including carry portfolios, momentum portfolios, and a cross section of 39 currencies, were employed. Upon dividing our sample into high and low global economic risk states, we found that the spread of the zero-cost momentum strategy is larger and highly significant in high RD states compared to low RD states. Even after controlling for other risk factors in currency markets, our findings remain the same. Also, we found that the relation between momentum payoffs and global economics risk is linearly increasing in risk. Based on this evidence, we conclude global economic risk as proxied by RD helps to explain currency momentum profits.

It should be noted that developing a theoretical model linking equity and currency markets is beyond the scope of this paper. Future theoretical research on the association between

[18] The regression results are provided in appendix Table A.6.

currency and equity markets that takes into account RD is recommended. Also, empirical work on RD in other asset classes, such as real estate, commodities, and derivatives, is suggested.

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Table 1. Descriptive statistics

Panel A: Forward discount sorted portfolios and currency market risk factors

This table reports the descriptive statistics for six currency portfolios and for Lustig, Roussanov, and Verdelhan's (2011) currency risk factors. Portfolio and risk factor data are obtained from Hanno Lustig's website with sample period from 1983:11 to 2010:1. As in Lustig et al., the portfolios are constructed by sorting currencies into six groups at time t based on the one-month forward discount (i.e., nominal interest rate differential) at the end of period $t-1$. Portfolio 1 (6) contains currencies with the lowest (highest) interest rates. The dollar factor is an average of all six portfolios, whereas the carry factor is calculated as the difference between portfolios 6 and 1. All four moments are in monthly terms.

All Currencies								
	Portfolio						**Dollar**	**Carry**
Assets	**1**	**2**	**3**	**4**	**5**	**6**	**Factor**	**Factor**
Mean	-0.15 %	0.01 %	0.13 %	0.33 %	0.34 %	0.60 %	0.21 %	0.75 %
Std	2.38 %	2.14 %	2.21 %	2.19 %	2.43 %	2.80 %	2.00 %	2.62 %
Skewness	0.30	0.03	0.09	0.02	-0.41	-0.28	-0.23	-0.70
Kurtosis	1.26	1.45	1.01	2.63	2.07	1.79	0.72	1.61

Table 1, continued

Panel B: Spot changes of 39 U.S. dollar exchange rates

This table reports the descriptive statistics for 39 currency spot US dollar exchange rates. The data is the same as in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library with sample period from 1983:11 to 2010:1. All four moments are reported based on monthly data. The data set contains at most 37 different currencies of the following countries: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, the United Kingdom, and the Euro. The euro series start in January 1999 and all Euro area countries are excluded after this date. Some of the currencies have pegged their exchange rate partially or totally to the US dollar over the course of the sample. They remain in the sample because forward contracts were easily accessible to investors and their forward prices are not inconsistent with covered interest rate parity. Based on failures of covered interest rate parity, the following observations were deleted from the sample: South Africa from the end of July 1985 to the end of August 1985; Malaysia from the end of August 1998 to the end of June 2005; Indonesia from the end of December 2000 to the end of May 2007; Turkey from the end of October 2000 to the end of November 2001; and United Arab Emirates from the end of June 2006 to the end of November 2006.

Currencies	**AUS**	**AUT**	**BEL**	**CAN**	**HKG**	**CZE**	**DNK**	**EUR**	**FIN**	**FRA**	**DEU**	**GRC**	**HUN**	**IND**	**IDN**	**IRL**	**ITA**	**JPN**	**KWT**
Mean	-0.02 %	0.07 %	-0.67 %	-0.07 %	0.00 %	-0.25 %	-0.25 %	-0.15 %	0.16 %	-0.32 %	-0.38 %	0.36 %	0.09 %	0.16 %	0.88 %	0.28 %	-0.10 %	-0.34 %	-0.03 %
Std	3.47 %	2.52 %	3.47 %	2.03 %	0.15 %	3.79 %	3.19 %	3.19 %	2.60 %	2.60 %	3.38 %	3.30 %	3.96 %	1.71 %	8.89 %	2.57 %	3.26 %	3.32 %	0.78 %
Skewness	0.89	0.07	-0.08	0.62	-0.40	0.25	0.21	0.21	0.19	0.19	0.21	1.22	1.07	0.43	2.70	0.10	0.68	-0.36	1.62
Kurtosis	3.31	-0.26	-0.39	7.02	5.61	0.23	0.61	0.61	-0.16	-0.16	0.27	3.03	4.49	3.76	20.23	-0.03	1.93	1.44	16.21
Data starts	01.85	02.97	12.83	01.85	12.83	02.97	01.85	02.99	02.97	12.83	12.83	02.97	02.97	02.97	02.97	02.97	12.83	12.83	02.97
Data ends	12.10	12.98	11.91	12.10	12.10	12.10	12.10	12.10	12.98	12.98	12.98	12.98	12.10	12.10	12.10	12.98	12.98	12.10	12.10

Currencies	**MYS**	**MEX**	**NLD**	**NZL**	**NOR**	**PHL**	**POL**	**PRT**	**SAU**	**SGP**	**ZAF**	**KRW**	**ESP**	**SWE**	**CHE**	**TRY**	**THA**	**TUR**	**ARE**	**GBR**
Mean	0.11 %	0.32 %	-0.38 %	-0.13 %	-0.14 %	0.36 %	-0.02 %	0.17 %	0.00 %	-0.15 %	0.44 %	0.19 %	0.10 %	-0.06 %	-0.30 %	0.10 %	0.16 %	1.64 %	0.00 %	-0.11 %
Std	3.05 %	2.70 %	3.37 %	3.52 %	3.17 %	2.79 %	3.99 %	2.46 %	0.10 %	1.53 %	4.46 %	5.07 %	2.48 %	3.31 %	3.44 %	1.70 %	3.71 %	5.20 %	0.05 %	3.04 %
Skewness	4.69	1.34	0.19	0.42	0.61	1.45	0.76	0.11	3.04	0.11	0.43	2.40	0.05	0.55	-0.13	0.14	0.90	1.82	0.50	0.28
Kurtosis	63.51	5.15	0.27	2.75	1.73	5.69	2.01	-0.12	62.57	2.21	2.48	18.36	-0.20	1.81	0.45	3.74	13.64	10.71	77.60	2.53
Data starts	01.85	02.97	12.83	01.85	01.85	02.97	02.97	02.97	02.97	01.85	12.83	02.97	02.97	01.85	12.83	02.97	02.97	02.97	02.97	12.83
Data ends	12.10	12.10	12.98	12.10	12.10	12.10	12.10	12.98	12.10	12.10	12.10	12.10	12.98	12.10	12.10	12.10	12.10	12.10	12.10	12.10

Table 1, continued

Panel C: Excess returns on currency momentum

This table reports the descriptive statistics for six momentum portfolios sorted by the previous month return. The data are downloaded from the *Journal of Financial Economics* data library and are the same as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) with sample period from 1983:11 to 2010:1. As in Menkhoff et al., the six momentum portfolios are contructed by sorting currencies for 48 US dollar exchange rates into six groups at time *t* based on the previous months return. Portfolio 1(6) contains currencies with the lowest (highest) monthly return.

Panel C

Mom **(1,1)**	**Low**	**2**	**3**	**4**	**5**	**High**
Mean	-0.22 %	0.05 %	0.14 %	0.32 %	0.33 %	0.62 %
Std	2.90 %	2.44 %	2.55 %	2.46 %	2.56 %	2.55 %
Skewness	-0.47	-0.86	-0.44	-0.38	-0.59	0.09
Kurtosis	3.75	4.43	1.99	1.45	3.94	0.53

Table 2. Momentum and currency return dispersion

This table reports average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low return dispersion state. A period is classified as a low state (high state) if the estimated three-month moving average of the measure for currency RD is below (above) its median value. We employ three moving average representations of three different measures of currency RD denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) as well as the first principal component, $PC_{C,13}$, to determine the currency RD states. The *t*-statistics are based on heteroscedasticity and autocorrelation consistent standard errors in Newey and West (1987). The columns headed High-Low test the hypothesis that the difference of the estimated parameters in the high state minus low state equals zero. The sample period is from 1984:2 to 2010:1.

Measure	**Long leg**			**Short leg**			**Long-Short**		
	High state	Low state	High-Low	High state	Low state	High-Low	High state	Low state	High-Low
$RD_{1,13}$	0.84***	0.44**	0.41	-0.36	-0.08	-0.28	1.20***	0.51***	0.69**
	(3.29)	(2.27)	(1.44)	(-1.21)	(-0.39)	(-0.82)	(4.38)	(2.64)	(2.11)
$RD_{2,13}$	0.58**	0.67***	-0.09	-0.59*	0.12	-0.35	1.17***	0.55***	0.62*
	(2.11)	(3.81)	(-0.31)	(-1.92)	(0.69)	(-0.96)	(3.90)	(3.42)	(1.90)
$RD_{3,13}$	0.86***	0.42**	0.44	-0.56**	0.11	-0.67**	1.43***	0.31**	1.11***
	(3.05)	(2.41)	(1.44)	(-2.05)	(0.57)	(-2.14)	(4.62)	(2.27)	(3.28)
$PC_{C,13}$	0.81***	0.47***	0.35	-0.58*	0.12	-0.69**	1.39***	0.35**	1.04***
	(2.99)	(2.62)	(1.20)	(-1.92)	(0.70)	(-2.10)	(4.58)	(2.28)	(3.11)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Table 3. Momentum and currency return dispersion controlling for risk factor in currency markets

This table reports risk-adjusted average excess returns for the MOM (1,1) strategy in months classified as representing a high or low return dispersion (RD) state. A period is classified as a low state (high state) if the estimated three-month moving average of the measure for currency RD is below (above) its median value. We employ three moving average representations of three different measures of currency RD denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) as well as the first principal component, $PC_{C,13}$, to determine the currency RD states. The risk-adjusted average excess returns are the intercept estimates of α_{High} and α_{Low} in the following regression:

$$R_{MOM,t} = \alpha_{High} d_{H,t} + \alpha_{Low} d_{L,t} + \beta_1 RX_t + \beta_2 CARRY_t + e_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low cross-sectional dispersion states, respectively, and $R_{MOM,t}$ is the excess return of the momentum spread in month t on either the long leg, the short leg, or their difference. Moreover, RX_t and $CARRY_t$ denote Lustig, Roussanov, and Verdelhan's (2011) dollar and carry risk factors in month t. The t-statistics are based on heteroscedasticity and autocorrelation consistent standard errors in Newey and West (1987). The columns headed High-Low test the hypothesis that the difference of the estimated parameters in the high state minus low state equals zero. The sample period is from 1984:2 to 2010:1.

Measure	**Long leg**			**Short leg**			**Long-Short**		
	High state	Low state	High-Low	High state	Low state	High-Low	High state	Low state	High-Low
$RD_{1,13}$	0.43***	0.10	0.32*	-0.81	-0.43	-0.38*	1.23***	0.53**	0.70**
	(2.71)	(0.88)	(1.78)	(-4.59)	(-3.05)	(-1.89)	(4.32)	(2.42)	(2.17)
$RD_{2,13}$	0.75***	0.29**	0.46**	-0.39	-0.29	-0.11	1.14***	0.57***	0.57*
	(4.21)	(2.51)	(2.54)	(-2.10)	(-2.40)	(-0.50)	(3.72)	(2.87)	(1.73)
$RD_{3,13}$	0.69***	0.00	0.69***	-1.17	-0.53	-0.64*	1.89*	0.59	1.29**
	(3.95)	(0.02)	(3.76)	(-1.59)	(-1.25)	(-1.79)	(1.94)	(1.07)	(2.52)
$PC_{C,13}$	0.88***	0.16	0.72***	-0.49*	-0.20*	-0.28	1.37***	0.36*	1.00***
	(4.79)	(1.43)	(3.60)	(-2.57)	(-1.90)	(-1.35)	(4.36)	(1.95)	(2.96)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Table 4. Momentum and relative currency return dispersion

This table reports average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low relative return dispersion (RRD) state. A period is classified as a low state (high state) if the estimated three-month moving average of the measure for relative currency return dispersion is below (above) its median value. We employ three moving average representations of three different measures of currency return dispersion denoted as $RRD_{1,13}$, $RRD_{2,13}$, $RRD_{3,13}$ (see equations (4) to (6) in the text) as well as the first principal component, $PC_{C,13}$, to determine the relative currency dispersion states. The *t*-statistics are based on heteroscedasticity and autocorrelation consistent standard errors in Newey and West (1987). The columns headed High-Low test the hypothesis that the difference of the estimated parameters in the high state minus low state equals zero. The sample period is from 1984:2 to 2010:1.

Measure	**Long leg**			**Short leg**			**Long-Short**		
	High state	Low state	High-Low	High state	Low state	High-Low	High state	Low state	High-Low
$RRD_{1,13}$	0.69***	0.57***	0.16	-0.28	-0.14	-0.14	0.97***	0.72***	0.26
	(2.93)	(2.73)	(0.42)	(-0.98)	(-0.71)	(-0.42)	(3.40)	(3.68)	(0.77)
$RRD_{2,13}$	0.77***	0.51***	0.26	-0.39	-0.04	-0.35	1.16***	0.55***	0.61*
	(2.67)	(2.71)	(0.80)	(-1.31)	(-0.21)	(-0.96)	(3.83)	(3.37)	(1.82)
$RRD_{3,13}$	0.88***	0.41**	0.48	-0.48*	0.03	-0.51	1.36**	0.37**	0.99***
	(3.16)	(2.04)	(1.45)	(-1.84)	(0.15)	(-1.51)	(4.42)	(2.34)	(2.83)
$PC_{C,13}$	0.93***	0.36*	0.56*	-0.41	-0.03	-0.38	1.33***	0.40***	0.94***
	(3.50)	(1.92)	(1.90)	(-1.43)	(-0.16)	(-1.12)	(4.39)	(2.75)	(2.82)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Table 5. Momentum payoffs during periods of low and high currency return dispersion in four states of the world

This table reports average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low return dispersion (RD) state. Periods were defined as in Petkova and Zhang (2005). State 1 (low state) corresponds to the 10% of lowest observations for RD; state 2 corresponds to below-average RD excluding the 10% lowest observations; state 3 corresponds to above-average RD excluding the highest 10% observations; and state 4 (high state) corresponds to the 10% highest observations for RD. We employ three moving average representations of three different measures of currency RD denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) as well as the first principal component, $PC_{C,13}$, to determine the currency RD states. The *t*-statistics are based on heteroskedasticity and autocorrelation consistent standard errors in Newey and West (1987). The sample period is from 1984:2 to 2010:1.

Measure	**State 1 (Low)**	**State 2**	**State 3**	**State 4 (High)**
$RD_{1,13}$	0.64	0.48**	1.19***	1.23**
	(1.50)	(2.44)	(4.09)	(1.98)
$RD_{2,13}$	0.36	0.59***	1.03***	1.70**
	(1.26)	(3.12)	(3.11)	(2.06)
$RD_{3,13}$	0.40**	0.29*	1.42***	1.43*
	(2.18)	(1.79)	(4.75)	(1.70)
PC_{RD}	0.06	0.41**	1.46***	1.13*
	(0.31)	(2.25)	(4.25)	(1.77)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Table 6. Risk-adjusted momentum payoffs during periods of low and high currency return dispersion in four states of the world

This table reports average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low relative dispersion state (RRD). The periods were as defined as in Petkova and Zhang (2005). State 1 (good state) corresponds to the 10% of lowest observations for RRD; state 2 corresponds to below-average RRD excluding the 10% lowest observations; state 3 corresponds to above-average RRD excluding the highest 10% observations; and state 4 (bad state) corresponds to the 10% highest observations for RRD. We employ three moving average representations of three different measures of currency RRD denoted as $RRD_{1,13}$, $RRD_{2,13}$, $RRD_{3,13}$ (see equations (4) to (6) in the text) as well as the first principal component, $PC_{C,13}$, to determine the relative currency dispersion states. The *t*-statistics are based on heteroscedasticity and autocorrelation consistent standard errors in Newey and West (1987). The sample period is from 1984:2 to 2010:1.

Measure	**State 1 (Low)**	**State 2**	**State 3**	**State 4 (High)**
$RRD_{1,13}$	0.40	0.79***	0.91***	1.20*
	(0.86)	(3.41)	(3.05)	(1.71)
$RRD_{2,13}$	0.03	0.66***	1.27***	0.74
	(0.07)	(3.63)	(3.67)	(1.08)
$RRD_{3,13}$	0.42	0.36**	1.16***	2.13***
	(1.62)	(2.04)	(3.88)	(2.59)
PC_{RRD}	0.56	0.36**	1.37***	1.20
	(1.25)	(2.16)	(4.10)	(1.56)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Figure 1. Different measures of cross-sectional currency return dispersion

This figure plots the three-months moving averages of three different measures of currency return dispersion denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) and the first principal component, $PC_{C,13}$. The sample period is from 1984:2 to 2010:1.

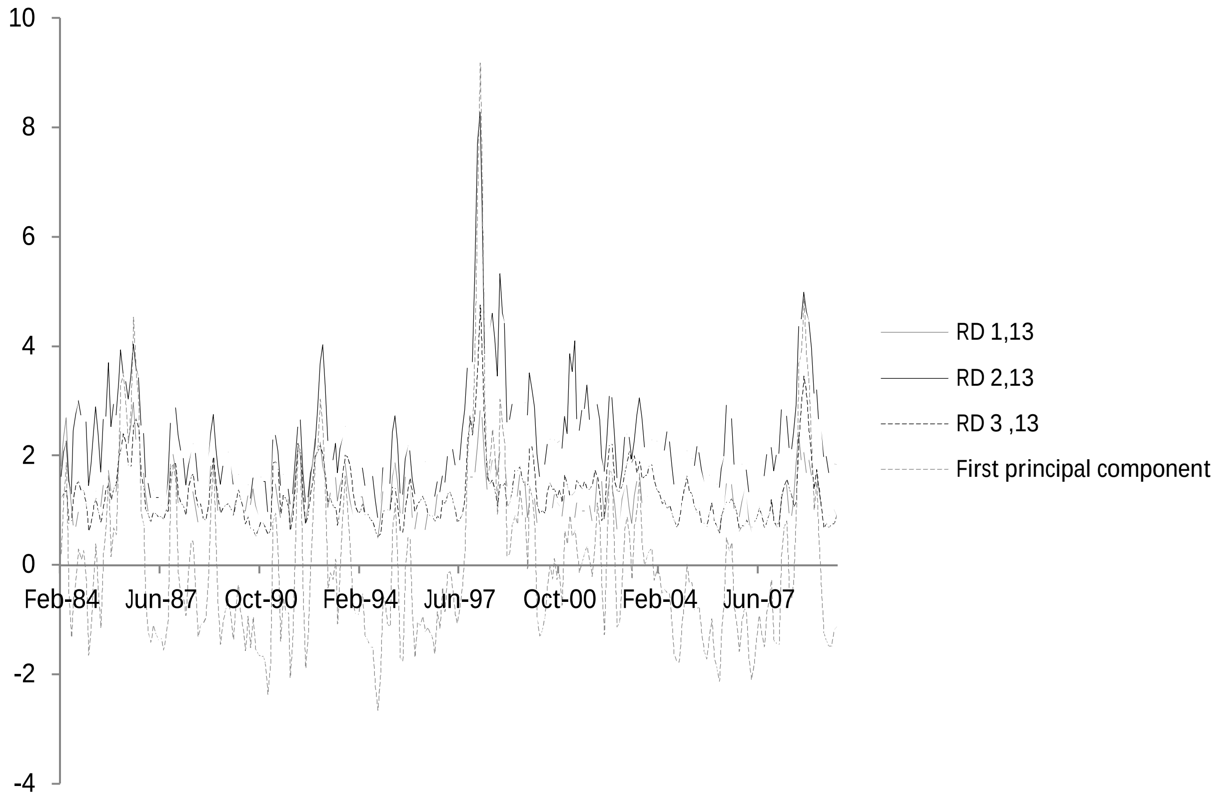


Figure 2. Cross-sectional currency return dispersion and periods of economic stress

This figure plots the three-months moving averages of three different measures of currency return dispersion denoted as $RD_{1,13}$ (see equations (1) in the text) and 10% of the observations where the level of cross-sectional RD was the highest. The Figure displays the corresponding world-economic evens that coincide with times of highest cross-sectional RD. The sample period is from 1984:2 to 2010:1.

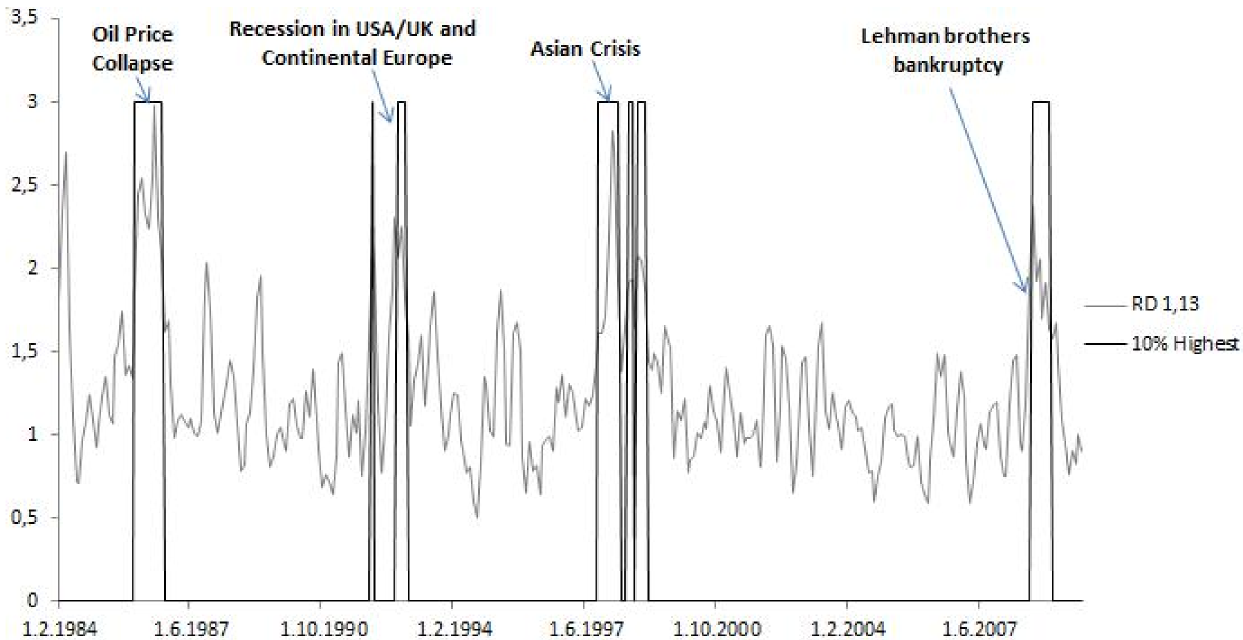


Figure 3. Cross-sectional currency return dispersion in global equity and currency markets

This figure plots the three-month moving average of the return dispersion in the currency market denoted as RD_{13}, three-month moving average of the return dispersion in the global equity market denoted as RD_{13}, and the first principal component. The sample period is from 1994:4 to 2010:1.

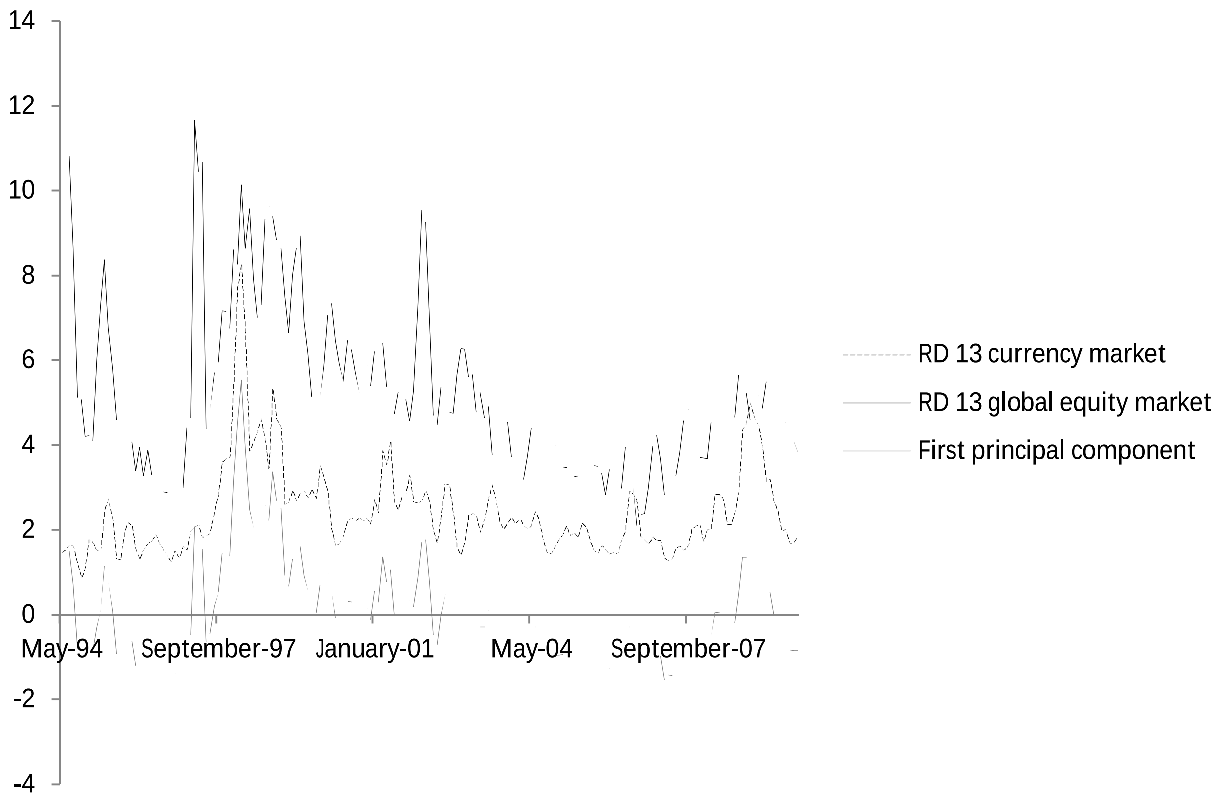
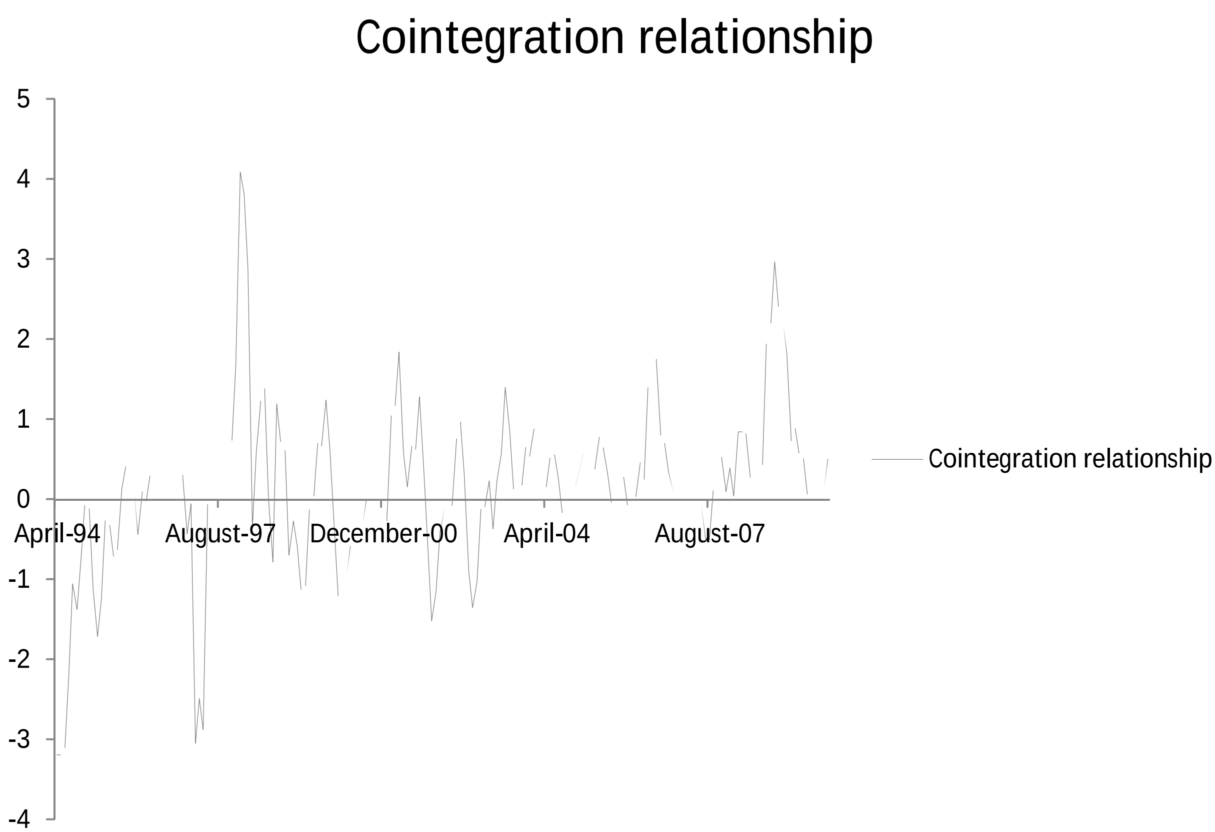


Figure 4. Cointegration relationship

This figure plots the residuals $\hat{u}_t$ of the following cointegration regression equation:

$$RD_{t,13}^{Currency}=\delta \cdot RD_{t,13}^{Equity} + u_t,$$

where $RD_{t,13}^{Currency}$ denotes the three-month moving average of RD_{2t}, and $RD_{t,13}^{Equity}$ is the three-month moving average of RD_t^{Equity}. The sample period is from 1994:4 to 2010:1.



Appendix

Table A.1. ADF tests for the whole sample

This table reports the ADF tests for the moving averages of three different currency return dispersion measures. The test statistics account for an intercept and 12 ($RD_{1,13}$), 10 ($RD_{2,13}$), and 7 ($RD_{3,13}$) lags based on the Schwarz criterion. The critical values for the 10%, 5%, and 1% significance levels are -2.57, -2.87, and -3.45, respectively. The corresponding *p*-values are given in parentheses. The sample period is from 1984:2 to 2010:1.

ADF test statistic type	$\boldsymbol{RD_{1,13}}$	$\boldsymbol{RD_{2,13}}$	$\boldsymbol{RD_{3,13}}$
Including intercept	-3.74*** (0.00)	-3.91*** (0.00)	-5.00*** (0.00)

***Statistically significant on a 1% level.

Table A.2. ADF tests for a subsample

This table reports the ADF tests for the moving averages of three different currency return dispersion measures. The test statistics account for an intercept and 9 ($RD_{t,13}^{Currency}$) and 3 ($RD_{t,13}^{Equity}$) lags based on the Schwarz criterion. The critical values for the 10%, 5%, and 1% significance levels are -2.57, -2.87, and -3.45, respectively. The corresponding *p*-values are given in parentheses. The sample period is from 1994:4 to 2010:1.

ADF test statistic type	$\boldsymbol{RD_{t,13}^{Currency}}$	$\boldsymbol{RD_{t,13}^{Equity}}$
Including intercept	-2.62* (0.09)	-2.77* (0.06)

*Statistically significant on a 10% level.

Table A.3. Descriptive statistics for excess returns on the currency momentum strategy employing different data sets

This table reports the descriptive statistics for the winner and loser currency portfolios of the momentum strategy, the dollar and carry risk factors, and the spread between the winner and loser portfolios in the formation period. To implement the momentum strategy, we use 39 currency spot US dollar exchange rates (see Panel B in Table 1). The data is the same as in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library with sample period from 1984:2 to 2010:1. Panel A reports the descriptive statistics for portfolios sorted by past returns employing Verdelhan's data set. Panel B reports the statistics for Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) data set.

Panel A: Descriptive statistics employing Verdelhan's (2012) data set

	Loser	**PG 2**	**PG 3**	**PG 4**	**PG 5**	**Winner**
Mean	-0.19%	0.04%	0.15%	0.34%	0.29%	0.54%
Std	2.86%	2.46%	2.49%	2.41%	2.53%	2.58%
Skewness	-0.76	-0.73	-0.40	-0.10	-0.44	0.21
Kurtosis	4.59	3.55	3.36	0.63	2.66	1.33

Panel B: Descriptive statistics employing Menkhoff et al.'s (2012a) data set

	Loser	**PG 2**	**PG 3**	**PG 4**	**PG 5**	**Winner**
Mean	-0.22%	0.05%	0.14%	0.32%	0.33%	0.62%
Std	2.90%	2.44%	2.55%	2.46%	2.56%	2.55%
Skewness	-0.47	-0.86	-0.44	-0.38	-0.59	0.09
Kurtosis	3.75	4.43	1.99	1.45	3.94	0.53

Table A.4. Descriptive statistics for risk factors using different data sets

This table reports the descriptive statistics for both the dollar (DOL) and carry risk (CAR) factors employing different data sets. The data set *Verdelhan* account for 39 currency spot US dollar exchange rates (see Panel B in Table 1). The data are the same as in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library. The data set *Menkhoff et al.* is downloaded from the *Journal of Financial Economics* data library and is the same as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). The data set *Lustig et al.* is obtained from Hanno Lustig's website and is the same as in Lustig, Roussanov, and Verdelhan (2011). The data ranges from 1984:2 to 2010:1.

Data set	**Mean**		**Std**		**Skewness**		**Kurtosis**	
	DOL	CAR	DOL	CAR	DOL	CAR	DOL	CAR
Verdelhan	0.21%	0.69%	2.09	2.83	-0.40	-0.79	0.92	1.50
Menkhoff et al.	0.20%	0.86%	2.19	2.63	-0.39	-0.66	1.16	1.30
Lustig et al.	0.21%	0.75%	2.00	2.62	-0.23	-0.70	0.72	1.61

Table A.5. Momentum and currency return dispersion controlling for risk factors in currency markets

This table reports risk-adjusted average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low return dispersion (RD) state. A period is classified as a low state (high state) if the estimated three-month moving average of the measure for currency RD is below (above) its median value. We employ three moving average representations for three different measures of currency RD denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) as well as the first principal component, $PC_{C,13}$, to determine the currency RD states. The risk-adjusted average excess returns are the intercept estimates of α_{High} and α_{Low} in the following regression:

$$R_{MOM,t} = \alpha_{High} d_{H,t} + \alpha_{Low} d_{L,t} + \beta_1 RX_t + \beta_2 CARRY_t + \beta_3 FSPREAD_{t-1} + e_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low cross-sectional dispersion states, respectively, and $R_{MOM,t}$ is the excess return of the momentum spread in month *t* on either the long leg, the short leg, or their difference. Moreover, RX_t and $CARRY_t$ denote Lustig, Roussanov, and Verdelhan's (2011) dollar and carry risk factors in month *t*, respectively, and $FSPREAD_{t-1}$ is the spread between winner and loser currency portfolios in the formation period. The momentum payoffs, the corresponding spread in past returns, and risk factors are compounded employing Verdelshan's data set (see Panel B in Table 1). The *t*-statistics are based on heteroskedasticity and autocorrelation consistent standard errors in Newey and West (1987). The columns headed High-Low test the hypothesis that the difference of the estimated parameters in the high state minus low state equals zero. The sample period is from 1984:2 to 2010:1.

Measure	**Long leg**			**Short leg**			**Long-Short**		
	High state	Low state	High-Low	High state	Low state	High-Low	High state	Low state	High-Low
$RD_{1,13}$	1.78***	0.86**	0.93***	-1.74***	-1.10	-0.64***	3.52***	1.96***	1.56***
	(3.29)	(2.21)	(3.11)	(-4.54)	(-3.95)	(-3.06)	(5.07)	(3.69)	(4.22)
$RD_{2,13}$	1.61**	0.97**	0.63	-1.52***	-1.18***	-0.34	3.14***	2.17***	0.97**
	(2.28)	(2.35)	(1.61)	(-3.09)	(-3.94)	(-1.29)	(3.45)	(3.81)	(2.04)
$RD_{3,13}$	1.91***	0.94**	0.97***	-1.50***	-1.15***	-0.35	3.41***	2.09***	1.32***
	(3.14)	(2.40)	(3.05)	(-3.40)	(-4.00)	(-1.39)	(4.12)	(3.90)	(3.19)
$PC_{C,13}$	1.75***	0.96**	0.79**	-1.86***	-1.18***	-0.68***	3.61***	2.14***	1.47***
	(2.82)	(2.42)	(2.31)	(-4.25)	(-4.22)	(-2.82)	(4.46)	(4.03)	(3.40)

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Table A.6. Controlling for dispersion in formation period returns

This table reports risk-adjusted average excess returns for the *MOM* (1,1) strategy in months classified as representing a high or low return dispersion (RD) state. A period is classified as a low state (high state) if the estimated three-month moving average of the measure for currency RD is below (above) its median value. We employ three moving average representations for three different measures of currency RD denoted as $RD_{1,13}$, $RD_{2,13}$, $RD_{3,13}$ (see equations (1) to (3) in the text) as well as the first principal component, $PC_{C,13}$, to determine the currency RD states. The risk-adjusted average excess returns are the intercept estimates of α_{High} and α_{Low} in the following regression:

$$R_{MOM,t} = \alpha_{High} d_{H,t} + \alpha_{Low} d_{L,t} + \beta_1 RX_t + \beta_2 CARRY_t + \beta_3 FSPREAD_{t-1} + e_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low cross-sectional dispersion states, respectively, and $R_{MOM,t}$ is the excess return of the momentum spread in month *t*. RX_t and $CARRY_t$ denote Lustig, Roussanov, and Verdelhan's (2011) dollar and carry risk factors in month *t*, respectively, and $FSPREAD_{t-1}$ is the spread between winner and loser currency portfolios in the formation period. The momentum payoffs, the corresponding spread in past returns and risk factors are compounded employing Verdelshan's data set (see Panel B in Table 1). The *t*-statistics are based on heteroskedasticity and autocorrelation consistent standard errors in Newey and West (1987). The sample period is from 1984:2 to 2010:1.

Measure	α_{High}	α_{Low}	β_1	β_2	β_3	R-squared
$RD_{1,13}$	3.52***	1.96***	-0.87***	-0.13**	-0.28***	0.31
	(5.07)	(3.69)	(-11.31)	(-1.97)	(-3.27)	
$RD_{2,13}$	3.14***	2.17***	-0.84***	-0.12*	-0.27***	0.29
	(3.45)	(3.81)	(-10.84)	(-1.68)	(-2.62)	
$RD_{3,13}$	3.41***	2.09***	-0.85***	-0.14*	-0.28***	0.30
	(4.12)	(3.90)	(-10.76)	(-1.94)	(-2.98)	
$PC_{C,13}$	3.61***	2.14***	-0.85***	-0.12*	-0.31***	0.31
	(4.45)	(4.03)	(-11.05)	(-1.75)	(-3.26)	

*Statistically significant on a 10% level.
**Statistically significant on a 5% level.
***Statistically significant on a 1% level.

Figure A.1. Cross-sectional currency return dispersion and formation period spread

This figure plots the three-months moving averages of the first principal component for three different measures of currency return dispersion and the spread between winner and loser currency portfolios in the formation period. The sample period is from 1984:2 to 2010:1.