Is momentum in currency markets Driven by global economic risk?

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Abstract

This article documents a robust link between the returns of the momentum anomaly implemented in currency markets and global economic risk, measured by the currency return dispersion (RD). We find the spread of the zero-cost momentum strategy to be significantly larger in high RD states compared to low RD states. The relation between momentum payoffs and global economic risk appears to increase linearly in risk. Notably, the results provide strong evidence that the same global economic risk component is present in equity markets.

Keywords: Return dispersion, Momentum, Currency markets, Global economic risk

JEL classification: G12, G14

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[1] We received insightful comments from Peter Nyberg.

1 Introduction

The interpretation of the momentum anomaly, as first documented in Jegadeesh and Titman (1993), has sparked intense debate in the academic literature. The explanations for this phenomenon typically fall into one of two categories: mispricing or risk; yet, even after more than two decades of research, consensus remains elusive.[1] While most studies focus on investigating the momentum anomaly in equity markets, surprisingly little attention has been paid to exploring what drives the momentum anomaly in foreign exchange markets, even though Menkhoff et al. (2012a) have highlighted that FX markets are more liquid than equity markets and feature enormous transaction volumes and low trading costs. Moreover, investors in FX markets typically do not face short-selling constraints that would prevent the shorting of past loser assets.

In two recent studies, Chichernea et al. (2014, 2015) established a robust link between cross-sectional return dispersion and the accrual anomaly in both stock and bond markets and investment related anomalies. The authors employ cross-sectional return dispersion as a macro state variable that caches general investing conditions faced by firms, as suggested by Gomes et al. (2003) and Zhang (2005). Conolly and Stivers (2003) found momentum in consecutive weekly equity-index returns when the latter week had abnormally high firm-level return dispersion and reversals consecutive equity-index returns when the latter week has abnormally low dispersion, indicating that cross-sectional stock return dispersion appears to be associated with momentum payoffs in equity markets. It may be surprising that there is no study available investigating the relation between cross-sectional currency return dispersion and momentum payoffs in currency markets, which are notably larger than equity markets in terms of trading volume.

The purpose of this study is to investigate whether the momentum anomaly in currency markets in line with Menkhoff et al. (2012a, 2012b), Burnside et al. (2011) and Moskowitz et al. (2012) may be driven by global economic risk. In doing so, it employs different measures of cross-sectional currency return dispersion (RD) that are assumed to capture general global economic conditions. If the payoffs of the momentum strategy are associated with global economic risk, and RD captures global macroeconomic conditions, we hypothesize that the momentum payoffs would be significantly higher in states of high global economic risk. We make use of various different measures of cross-sectional dispersion in asset returns and employed them successively in our analysis. In doing so, we sort the observations of cross-

[1] We direct readers to Menkhoff et al. (2012a) for a detailed discussion on this vast literature.

sectional currency return dispersion into above and below-median values indicating high and low dispersion regimes which, in turn, are interpreted as states of economic stress and ease, respectively. This approach is closely related to that of Stambaugh et al. (2012), who investigated the relation between investor sentiment and cross-sectional anomalies in the US equity market. In a regression analysis, the long and short legs of the momentum strategy are regressed on dummy variable models to test whether the strategy's payoffs depend on the state of the world economy. To check robustness, we also used the innovations of a model that uses the market-adjusted returns of cross-sectional currency dispersion and repeated the analysis.

We further hypothesize that whether cross-sectional currency return dispersion captures global economic risk, this risk should also be present in global equity markets. To answer this question, we estimate cross-sectional dispersion in global equity markets using a set of domestic country index futures. A principal component analysis was employed to investigate whether the variation in cross-sectional dispersion in global equity and currency markets can be explained by a dominant factor. In a robustness check, we also investigate whether the dispersion processes in those different markets are cointegrated. The presence of cointegration would imply a long-term relationship between these two different markets.

Our findings contribute to the existing literature in the following respects. We believe this paper is the first to document a robust link between the returns of the momentum anomaly in currency markets and global economic risk. For internationally aligned investors, it is most important to uncover the risks associated with their investment strategies. For example, our findings may help better understand the economic implications of dispersion in currencies. Moreover, our findings address how currency and equity markets are linked together. Karolyi and Stulz (2003) pointed out that numerous studies have attempted to uncover the link between currency and equity markets, but have either failed to find a robust link between those markets or found the relationship weaker than predicted by theory. This phenomenon has been referred to as the *stock-return/exchange-risk puzzle* by Armstrong et al. (2012).[2] This study sheds new light on the dynamic interactions between currency and global equity markets. In turn, our results suggest that theory may need to incorporate the link between currency and equity markets, although the theory is directed at understanding market-level return behavior.

Extending the existing research on risk-based explanations, the current research establishes a robust link between cross-sectional currency dispersion and momentum payoffs. Under global economic stress, the momentum payoffs are considerably larger than in times when

[2] A detailed overview about the literature that discusses how equity and currency market may be linked together is provided in Armstrong et al. (2012).

the global economy is quiet. Specifically, our findings indicate that the relation between momentum payoffs and an increase in global risk appears to be linear, and those findings are supported by various robustness checks. By providing a risk-based explanation for the momentum phenomenon in currency markets, the current research extends that of Conolly and Stivers (2003), who documented a link between stock returns and cross-sectional stock price dispersion. Employing a principal component analysis of cross-sectional dispersion in global equity markets and currency markets provides new evidence that these risk factors share a common component. Our findings complement Grobys' (2015) recent study revealing a link between currency and equity markets documenting that the volatility of those markets are driven by a common factor in times of economic stress. We argue that the spread between the cross-sectional return dispersion in global equity and currency markets is a mean-reverting stationary process which, in turn, implies that the same global risk component that drives return dispersion in currencies is also present in global equity markets.

This 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 et al. (2012a) highlighted how FX markets are more liquid than equity markets and feature considerable transaction volumes while involving low transaction costs. Moreover, 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 in practice. As a result, momentum strategies implemented in FX markets notably lowers 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. The profitability of these strategies has been shown to be short lived as more traders learn to exploit them. An extensive summary of this literature is provided by Menkhoff and Taylor (2007).

Some evidence on the existence for cross-sectional momentum profits in the FX market was provided by Okunev and White (2003). In a more recent paper, Asness et al. (2013) reported profitable momentum strategies across asset classes and geographical markets. Implemented in the currency market, they focused on the G10-space and used the cumulative past 12 months returns (and skipping the most recent month) to implement currency momentum strategies in order to maintain coherence in their analysis among asset classes. On the other hand, Burnside et al. (2011), Lustig et al. (2009), Menkhoff et al. (2012a, 2012b) and Moskowitz et al. (2012) employed a one-month formation period associated with a corresponding one-month holding period when implementing momentum-based trading strategies in currency markets.

Specifically, Menkhoff et al. (2012a) used a sample period from January 1976 to January 2010 for analyzing momentum strategies in a cross-section of up to 48 currencies. Their study employed one-month forward and spot data to implement momentum strategies. Their findings indicate that the payoffs of currency momentum strategies are the largest for a holding period of h=1 month, irrespective of the formation period. Furthermore, they investigated formation periods of f=1, 6, and 12 months, respectively. The results of their study show that the momentum strategy based on a one-month formation period, which is henceforward referred to as *MOM* (1,1), is the best performer in terms of both excess return and Sharpe ratio. Furthermore, they found that the momentum payoffs are mainly driven by spot moves. Even though these three momentum strategies are slightly correlated, there does not appear to be any significant correlation between those strategies and NBER recessions. More importantly, even though high-momentum currencies tend to have higher interest rates, momentum strategies implemented in currency markets and carry strategies are very different. Lustig et al. (2011) and Menkhoff et al. (2012a) document that the return correlations between the spreads of these two strategies are small and sometimes even negative.

Moreover, Burnside et al. (2011) used 20 major currencies over the sample period 1976-2010 to implement *MOM* (1,1). The results of their study show 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 a Sharpe ratio of 0.62. The strategy's payoffs are found to be slightly positively skewed which is also shown in Menkhoff et al.'s (2012a) study.

Since the vast majority of the momentum literature related to currency markets focuses exclusively on the *MOM* (1,1) strategy, we follow this path in the literature and whether the existence of momentum profits in currency markets may be explained by changes in global economic risk.

3 Data

The literature related to the equity market employs different types of measures for compounding cross-sectional stock return dispersion (RD). On the one hand, Maio (2013) and Stivers and Sun (2010) employed equity stock portfolios for their calculations. More precisely, 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 the noise associated with illiquid or small stocks and other extreme outliers is mitigated. On the other hand, Chichernea et al. (2014) and Jiang (2010) used individual stocks listed on the NYSE and AMEX and excluded the stocks in the lowest size decile. Chichernea et al. (2014, p5.) argued that a measure that is based on the full universe of individual stocks is more informative for the cross section of stock returns.

Since there is as yet no consensus on which type of measure is most adequate to compound the RD, we employed three different methods to calculate the cross-sectional RD in currency returns. The first measure is in line with Maio (2013), and Stivers and Sun (2010) and 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

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

where $R_{i,t}^{Carry}$ denotes the excess return of portfolio i sorted by local interest rates at time t and N=6.[3] The second measure makes use of individual currencies. In computing the second measure we followed Chichernea et al. (2014) and Jiang (2010) and downloaded a set of 39 individual currencies from Adrien Verdelhan's website. Then, we compounded the second measure for cross-sectional currency RD as

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

[3] 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.

where $R_{j,t}^{Spot}$ is the sport exchange rate of currency j at time t and M=39.[4] Finally, we also employ portfolios sorted by momentum. We used the same data for the one-month formation and one-month holding periods used in Menkhoff et al. (2012) and compound the third measure for cross-sectional currency RD as

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

where $R_{k,t}^{Momentum}$ denotes the excess return of portfolio k (sorted by their past month returns) at time t and K=6.[5] As we match the monthly data sets with each other, we operate with data running from 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. A visual inspection shows that they follow very similar time series paths. In addition, we estimate market-adjusted versions of RD denoted as relative return to dispersion (RRD) and given by

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

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

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

Our measures of RRD are similar to the relative stock return dispersion measure employed in Chichernea et al. (2014), who state that an RRD measure is orthogonal to the ordinary monthly market return and the absolute market return.

In order to compound the cross-sectional return dispersion of global equity markets, we used the same sample of data for domestic equity indices as was used in Grobys' (2014) study which accounts for 21 different stock indices.[6] We compounded the returns of these stock indices in their domestic currencies. Each stock index was interpreted as a well-diversified basket of

[4] The data are available at http://web.mit.edu/adrienv/www/Data.html.
[5] 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.
[6] Table 1 in Grobys (2014) presents an overview of the domestic stock indices employed.

large stocks to preclude having to sort these indices further into portfolios. As a result, the corresponding measure for cross-sectional global equity market dispersion is then given by

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

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

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

We matched the data set for currency and equity markets so that our data for RD_t^{Equity} runs from April 1994 to January 2010.

Finally, we use the same data for the momentum strategy based on a one-month formation and one-month holding period as employed in Menkhoff et al.'s (2012a) study. Matching the data sets used in previous studies ensured a high degree of coherence. Consequently, 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 in portfolio 6 and short in portfolio 1. The summary statistics for the retrieved data are reported in Table 1.

4 Empirical analysis

4.1 Currency return dispersion and expected returns

The methodology used to investigate the relation between currency return dispersion and the momentum anomaly is close to the research set-up adopted by Stambaugh et al. (2012) who investigated the association between investor sentiment and various cross-sectional asset pricing anomalies in the US stock market. The two major differences between the earlier Stambaugh et al. (2012) work and our paper are as follows: First, the earlier work incorporated investor sentiment and divided the observations into above and below-median values, indicating high and low investor sentiment. In contrast, the current research employed cross-sectional currency return dispersion as the corresponding sorting variable divided into above and below-median values, indicating high and low RD. Second, Stambaugh et al. (2012) interpreted the effects of investor sentiment as a behavioral-type explanation for a subset of asset pricing anomalies. However, we interpret cross-sectional currency return dispersion as a global risk factor, in a way similar to Chichernea et al. (2014, p.15), who argued that "RD is likely to capture the uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring".

Following Stambaugh et al. (2012), we start our analysis by classifying each month as following either a high-dispersion month or a low-dispersion month. To do so, we operate with a three-month moving average of our RD measures in Equations 1-3, as in Chichernea et al.'s (2014) study. Consequently, a high-dispersion month is one in which the value of the three-month RD is above its sample median value, and the low-dispersion months are those with below-median values. We compound average returns separately for the high- and low-sentiment months. Table 2 reports the results for the currency excess returns for our four different measures of RD as well as the first principal component.[7]

The results from Table 2 show that the spreads of the zero-cost momentum strategy are significantly larger in high RD states. More precisely, depending on the RD measure, the 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, indicating statistical significance on any level. In low RD states, the spreads are considerably lower, varying between 0.31 percent and 0.55 percent per month. A principal component analysis suggests that the three-months moving average of the three time series RD_1, RD_2 and RD_3 exhibit one dominant eigenvalue of 2.47.[8] The first principal component explains 82 percent of the variation in our three measures, suggesting that the underlying proxied risk is the same. Table 2 shows that when we employ the first principal component of the three measures for RD, the difference between high and low states of RD has an economic magnitude of 1.04 percent per month with a Newey-West (1987) *t*-statistic of 3.11. Interpreting states of high cross-sectional dispersion in currency returns as proxy for high global economic risk, the results strongly support a risk-based explanation for the existence of momentum payoffs in currency markets.

Lustig et al. (2011) proposed a two-factor asset pricing model consisting of a dollar risk factor and a carry risk factor. The dollar risk factor corresponds to the equal-weighted average of

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

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

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.[9] Hence, in order to check the robustness of our results, we included the two risk factors proposed by Lustig et al. (2011) in our regression model and repeated the previous analysis. After risk-adjustment, the results, as reported in Table 3, are virtually the same as in Table 2, supporting the previous finding. The difference of the risk-adjusted *MOM* (1,1) spread between bad and good states of the global economy is still 1.00 percent per month and statistically significant on any level.

As an additional robustness check of our results, we repeated the previous analysis and employed three-month moving averages of three different measures for relative currency return dispersion, as formulized in Equations 4-6. Our approach to compounding the relative currency return dispersion is similar to that found in Chichernea et al. (2014), who argued that an RRD measure is orthogonal to the simple monthly market return and the absolute market return. We also included the first principal component in our analysis. The results are reported in Table 4: Our conclusions remain unchanged.

Next, we scrutinized the relationship between RD and expected currency returns. In doing so, we followed Chichernea et al. (2014), and divided periods into four different states of the world, as did 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 in the previous analysis, when determining the states of the global economy we operated with the three-month moving average representations of RD. Average returns were computed as before. Furthermore, we performed the analysis for all three measures of RD as well as the first principal component. The results are reported in Table 5. We observed that in states 3 and 4 of the global economy, the momentum payoffs are always higher than in states 1 and 2. Using the three-month moving average of RD_2 as sorting variable, the spread is linear and strictly increasing as we move from state 1 to state 4. The linearity in payoffs confirms a risk-based explanation as the payoffs increase as the risk in the global economy rises.

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

To check the robustness of the results, as in Equations 4-6 we used relative currency return dispersion measures, as did Chichernea et al. (2014). Again, we employed the three-month moving averages of our RRD measures and repeated the previous analysis. The results are reported in Table 6: The conclusions do not change.

Another concern that could be raised is that the RD effect could be mechanically.[10] More precisely, a higher spread in the formation period might lead to higher momentum payoffs in the holding period. Consequently, our cross-sectional RD measures could simply pick up the dispersion in formation period returns. In Figure A.1 in the appendix, we plot the time series of the three-months moving averages of the first principal component of our three different measures of currency return dispersion and the spread between winner and loser portfolio in the formation period. The correlation is 0.68. To control for the dispersion in formation period returns, we included the spread between winner and loser period in the formation period in the regression for risk-adjustment and repeated the previous analysis. In doing so, we employed the same data used in Verdelhan (2012). We downloaded the data from Adrien Verdelhan's data library. This data set contains 39 currency spot USD-crosses, with the sample period ranging from 1983:11 to 2010:1. The data set is described in more detail in Table 1 Panel B. We compounded the momentum returns in the same manner as described in Menkfoff el al. (2012a, Section 3). In Table A.3 in the appendix, we report the 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. (2012a), the portfolios exhibit very similar properties. Since our spread is slightly lower, we consider our following analysis as being conservative.

In order to make the analysis coherent, we compounded also the dollar- and carry factors for the same data set. We compounded these risk factors as detailed in Lustig et al. (2011). In Table A.4 in the appendix, we compare 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, that we compounded using Verdelhan's (2012) data set, are very similar to those reported in the previous literature. Next, we included the spread between the past returns of the winner and loser portfolio of our *MOM* (1,1) strategy in the regression for risk adjustment. The loading against the spread of past returns is statistically significantly negative and increases the magnitude of the spread.[11] Controlling for dispersion in formation period returns, we repeated the previous analysis and tested whether the return differences between high and low dispersion states are statistically

[10] We thank Peter Nyberg for encouraging us to take this issue into account.
[11] The regression results are provided in Table A.6 in the appendix.

significantly larger than zero. The results are reported in Tables A.5 in the appendix and support the previous findings.

4.2 Does currency return dispersion measure global economic risk?

According to Chichernea et al. (2014), RD in the context of the stock universe may be interpreted as a measure for risk because it is likely to capture the uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring. Extended to the currency market, this risk should then capture global uncertainty. Therefore, we hypothesize that whether currency return dispersion captures global economic risk, the same risk component should also be present in global equity markets. In order to investigate this question, we first employed a principal component analysis of the three-months moving averages of RD_{2t} and RD_t^{Equity}. In doing so, we assumed that these time series are stationary.[12] Figure 2 plots the corresponding time series as well as the time series of the first principal component. A visual inspection of Figure 2 shows that both time series exhibit a similar trending behavior which is consequently also reflected in the time series related to the first principal component. The eigenvalue of the first principal component of the covariance matrix exhibits a magnitude of 1.50, being three times larger than the eigenvalue of the second principal component. As a result, the first principal component explains 75 percent of the variation. We interpret this as evidence of there being one dominant component that appears to be 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}. The first principal component of the covariance matrix explains 73 percent of the variation, confirming the previous finding.[13]

Employing principal component analysis requires stationarity of the time series analyzed. At that point we assumed that this condition was satisfied. Next, we tested the order of integration for the smaller sample period from April 1994 to January 2010. To do so, we employed the augmented Dickey-Fuller test (ADF) for the three-month moving averages $RD_{t,13}^{Currency}$ and RD_t^{Equity}. The results are reported in Table A.2 in the appendix and indicate that the time series do not exhibit stationarity on a common 5% level for the shorter sample period. We hypothesized that the currency and equity market would incorporate the same risk. If our hypothesis was true, and both time series are integrated, we would expect both time series to

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

share a common stochastic trend. In order to test this, we estimated the residuals $\hat{u}_t$ of the following cointegration regression equation,

$$RD_{t,13}^{Currency}=\delta \cdot RD_{t,13}^{Equity} + u_t, \qquad (8)$$

where $RD_{t,13}^{Currency}$ denotes the three-months moving average of RD_{2t} (which is also shown in Figures 1 and 2) and $RD_{t,13}^{Equity}$ is the three-months moving average of RD_t^{Equity}. In Figure 3, we plot the estimated residuals $\hat{u}_t$. Figure 3 shows that the residuals do not exhibit patterns of a linear trend even though there is not intercept included in cointegration regression. Then, we used ADF tests for testing for cointegration. The first test statistic does not account for deterministic terms while the second one accounts for an intercept term. The test statistics are estimated as -3.72 and -4.12. 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 $\hat{u}_t$ on any level. This result provides evidence that $RD_{t,13}^{Currency}$ and $RD_{t,13}^{Equity}$ are linked together in the long-term. In turn, the cointegration relationship implies that the same global economic risk component is present in both the currency market and the global equity market.[14]

5 Conclusion

This study is the first to document a robust link between the returns of the momentum anomaly in currency markets and global economic risk, measured by currency return dispersion. We applied several measures of cross-sectional currency RD (carry portfolios, momentum portfolios and a cross section of 39 currencies), which may capture general global economic conditions. By dividing our sample into high and low global economic risk states, we find the spread of the zero-cost momentum strategy to be significantly larger and highly statistically significant in high RD states compared to low RD states. Even when controlling for the two risk factors in currency markets, as proposed by Lustig et al. (2011), our findings remain virtually the same. Our results show that the relation between momentum payoffs and global economics risk appears to be

[14] 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}, that is $RD_{t,13}^{Currency}=\delta \cdot RD_{t,13}^{Equity} + u_t$ and tested the residuals again. The results remain unchanged.

linearly increasing in risk. Furthermore, a principal component analysis reveals the different currency RD measures to proxy the same underlying risk.

Furthermore, numerous studies have attempted to reveal the link between currency and equity markets, but either they failed to find a robust link between those markets or the relationship proved weaker than predicted by theory. We find that cross-sectional currency RD and cross-sectional global equity RD are in a cointegration relationship. We interpret this finding as evidence for global risk in currency and equity markets being driven by the same component. However, developing a new theoretical model that takes the documented link between currency and equity markets into account is beyond the scope of this paper. Future research extending theoretical models that account for this association between currency and equity markets is needed. Moreover, Grobys (2015) documents that the volatility between the US equity market and three different exchange-rates is driven only by the same component when the economy is weak. However, our findings indicate that the relation between cross-sectional dispersions in currencies and equities is not state-dependent, but follows the same path driven by a cointegration relationship. It is still unclear why the market volatilities behave differently from cross-sectional return dispersions.

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Table 1.

Panel A: Descriptive statistics for forward discount sorted portfolios and currency market risk factors

The table reports the descriptive statistics for six currency portfolios and for Lustig et al.'s (2011) currency risk factors. Portfolio and risk factor data were obtained from Hanno Lustig's website with the sample period ranging from 1983:11 to 2010:1. Lustig et al. (2011) constructed the portfolios 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 contains currencies with the lowest interest rates and portfolio 6 contains currencies with the highest interest rates. Dollar factor and carry factor are also as in Lustig et al. (2011), that is, the dollar factor is an average of all six portfolios, whereas the carry factor is calculated as a 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

Panel B: Descriptive statistics for spot changes of 39 U.S. dollar crosses

The table reports the descriptive statistics for 39 currency spot USD-crosses. The data is the same as used in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library, with the sample period ranging from 1983:11 to 2010:1. Panel B reports all first four moments calculated from 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; only the euro series remains. Some of the currencies have pegged their exchange rate partly or totally to the U.S. 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 the large 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; 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

Panel C: Descriptive statistics for currency Momentum strategy's excess returns

The table reports the descriptive statistics for six momentum portfolios sorted by the previous month return. The data were downloaded from the Journal of Financial Economics' data library and are the same as used in Menkhoff et al. (2012a) with the sample period ranging from 1983:11 to 2010:1. Menkhoff et al. (2012a), construct the six momentum portfolios by sorting currencies among 48 US dollar crosses into six groups at time *t* based on the previous months return. Portfolio 1 contains currencies with the lowest monthly return and portfolio 6 contains currencies with the 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

The table reports average returns in excess form of 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 1-3) as well as the first principal component, $PC_{C,13}$ to determine the currency RD states. The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The columns headed High-Low test the hypothesis in terms of whether the difference of the estimated parameters in the high state minus the estimated parameters in the low state is equal to 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

The table reports risk-adjusted average returns in excess form of 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 1-3) as well as the first principal component, $PC_{C,13}$ to determine the currency RD states. The risk-adjusted average returns in excess form of the *MOM*(1,1) strategy are the intercept estimates of α_{High} and α_{Low} in the 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, and $R_{MOM,t}$ is the excess return of the momentum spread in month *t* on either the long leg, the short leg, or the difference. Moreover, RX_t and $CARRY_t$ denote Lustig et. al.'s (2011) dollar and carry risk factors in month *t*. The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The columns headed High-Low test the hypothesis in terms of whether the difference of the estimated parameters in the high state minus the estimated parameters in the low state is equal to 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*** (2.71)	0.10 (0.88)	0.32* (1.78)	-0.81 (-4.59)	-0.43 (-3.05)	-0.38* (-1.89)	1.23*** (4.32)	0.53** (2.42)	0.70** (2.17)
$RD_{2,13}$	0.75*** (4.21)	0.29** (2.51)	0.46** (2.54)	-0.39 (-2.10)	-0.29 (-2.40)	-0.11 (-0.50)	1.14*** (3.72)	0.57*** (2.87)	0.57* (1.73)
$RD_{3,13}$	0.69*** (3.95)	0.00 (0.02)	0.69*** (3.76)	-1.17 (-1.59)	-0.53 (-1.25)	-0.64* (-1.79)	1.89* (1.94)	0.59 (1.07)	1.29** (2.52)
$PC_{C,13}$	0.88*** (4.79)	0.16 (1.43)	0.72*** (3.60)	-0.49* (-2.57)	-0.20* (-1.90)	-0.28 (-1.35)	1.37*** (4.36)	0.36* (1.95)	1.00*** (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

The table reports average returns in excess form of 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 4-6) as well as the first principal component, $PC_{C,13}$ to determine the relative currency dispersion states. The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The columns headed High-Low test the hypothesis in terms of whether the difference of the estimated parameters in the high state minus the estimated parameters in the low state is equal to 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 accounting for four states of the world

The table reports average returns in excess form of 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 1-3) as well as the first principal component, $PC_{C,13}$ to determine the currency RD states. The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of 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 accounting for four states of the world

The table reports average returns in excess form of 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 4-6) as well as the first principal component, $PC_{C,13}$ to determine the relative currency dispersion states. The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of 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 1-3) and the first principal component, $PC_{C,13}$. The sample period is from 1984:2 to 2010:1.

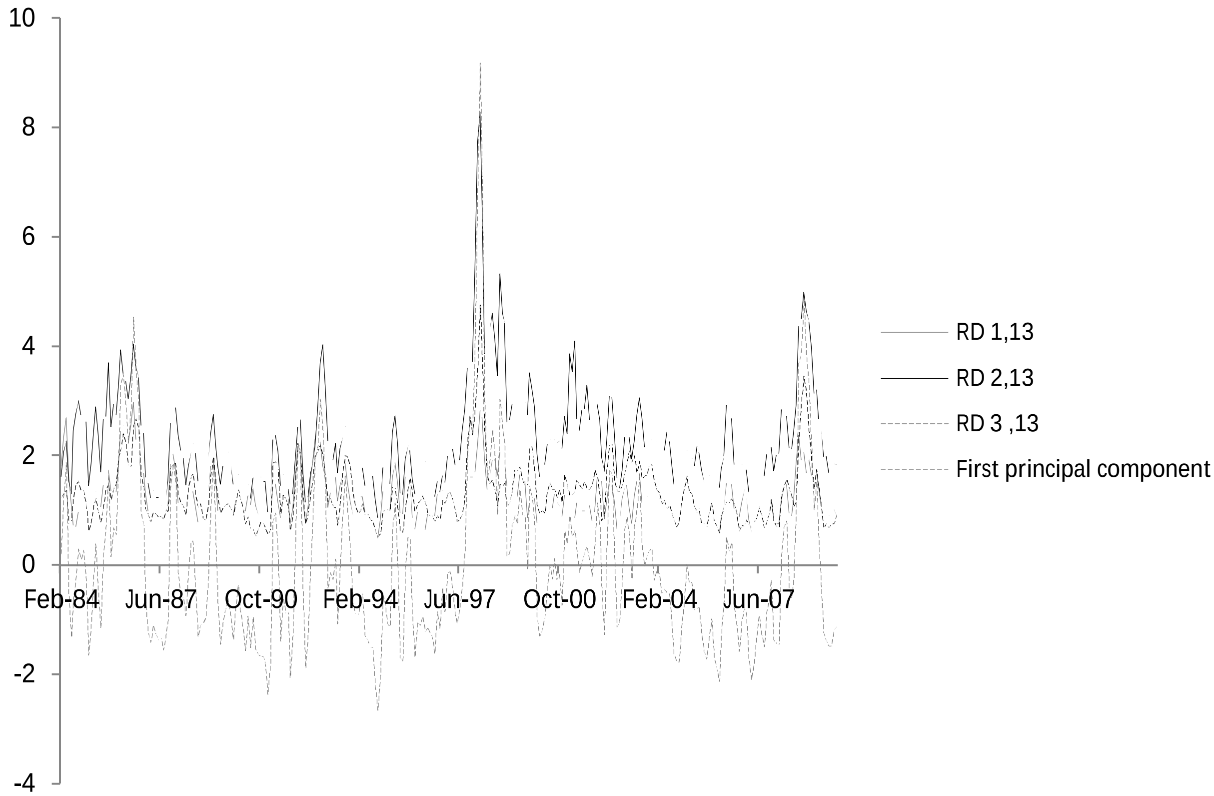


Figure 2. Cross-sectional currency return dispersion in global equity and currency markets

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

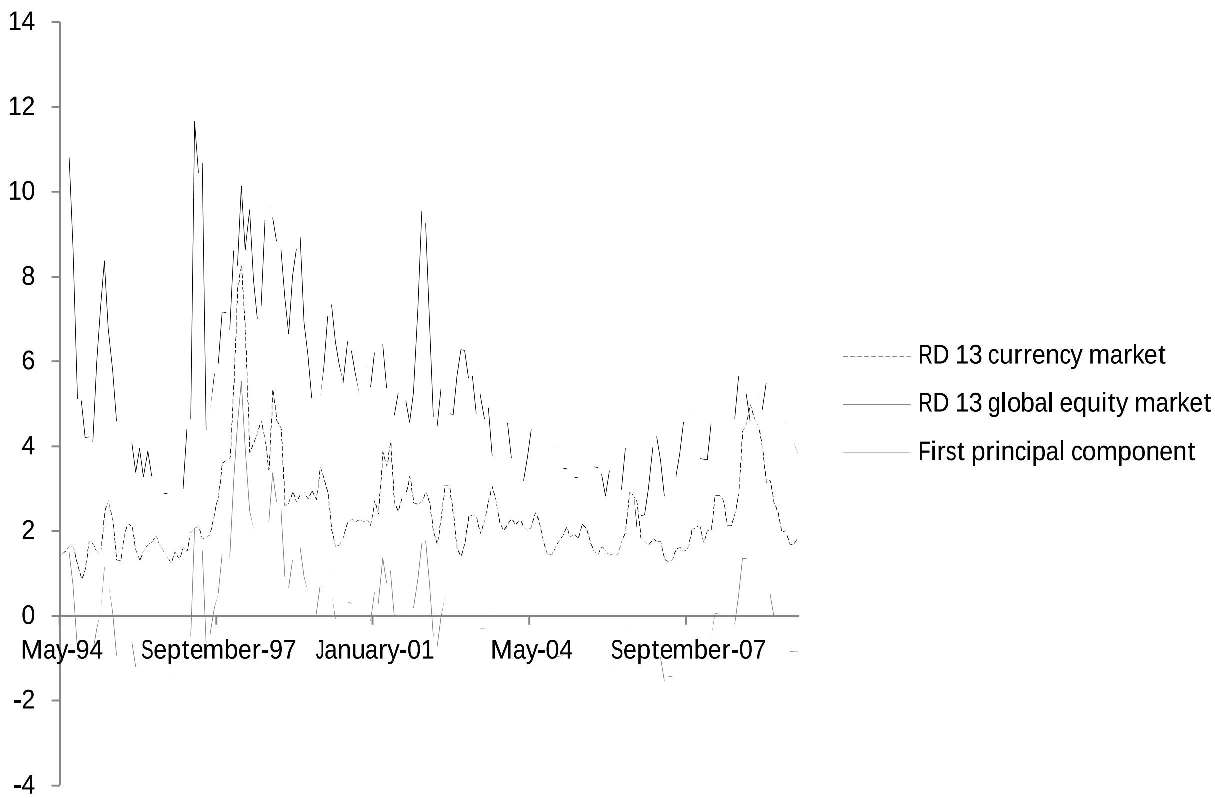
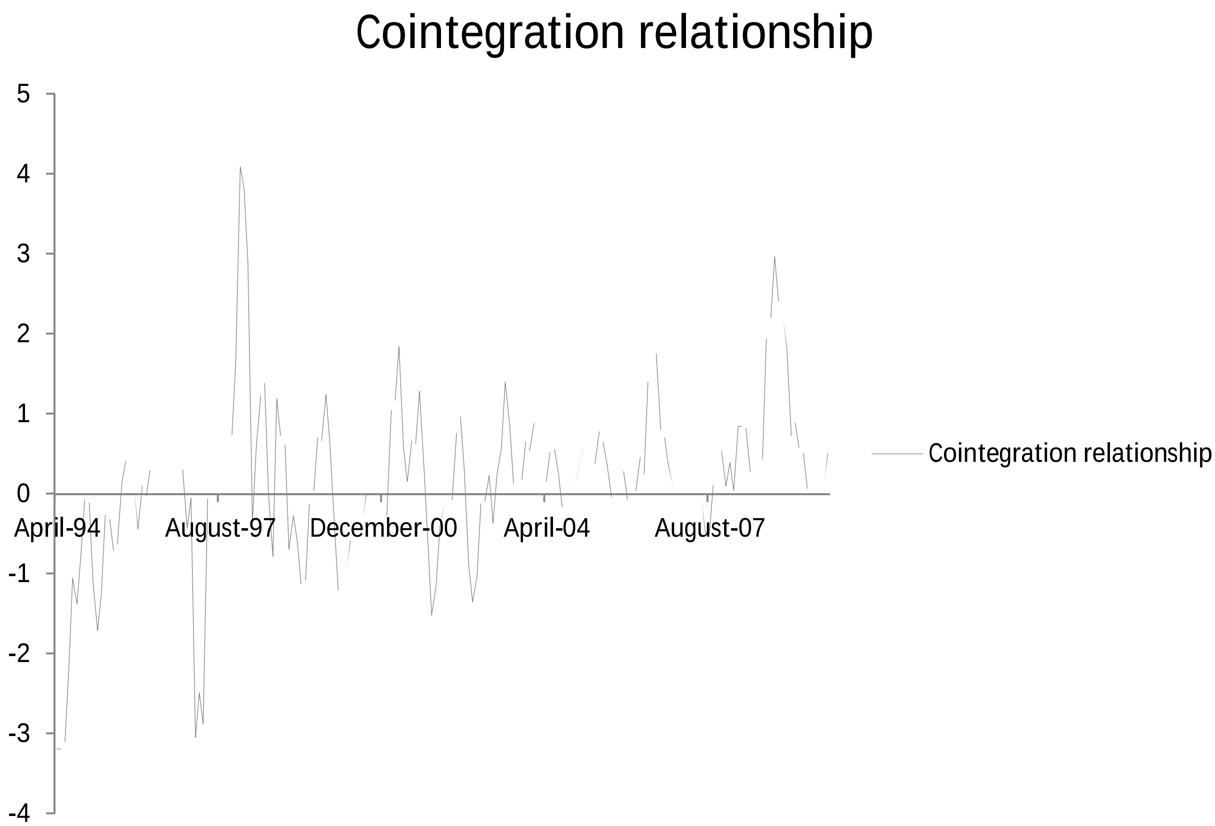


Figure 3. Cointegration relationship

This figure plots the residuals $\hat{u}_t$ of the 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 for 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 according to 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***	-3.91***	-5.00***
	(0.00)	(0.00)	(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 for 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 according to 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*	-2.77*
	(0.09)	(0.06)

*Statistically significant on a 10% level.

Table A.3. Descriptive statistics for currency Momentum strategy's excess returns employing different data sets

The table reports the descriptive statistics for the winner and loser portfolio of the momentum strategy implemented in currencies, the dollar and carry risk factors, and the spread between the winner and loser portfolio in the formation period. For implementing the momentum strategy, we used 39 currency spot USD-crosses (see Table 1 Panel B). The data is the same as used in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library, with the sample period ranging from 1984:2 to 2010:1. Panel A reports the descriptive statistics for portfolios sorted by past returns employing Verdelhan's data set and Panel B reports the statistics for Menkhoff et al.'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

The 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 USD-crosses (see Table 1 Panel B). The data are the same as used in Verdelhan (2012) and downloaded from Adrien Verdelhan's data library. The data set *Menkhoff et al*. were downloaded from the Journal of Financial Economics' data library and are the same as used in Menkhoff et al. (2012a).The data set *Lustig et al.* were obtained from Hanno Lustig's website and is the same as used in Lustig et al. (2011). The data sets are ranging 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 and

The table reports risk-adjusted average returns in excess form of 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 1-3) as well as the first principal component, $PC_{C,13}$ to determine the currency RD states. The risk-adjusted average returns in excess form of the *MOM*(1,1) strategy are the intercept estimates of α_{High} and α_{Low} in the 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, and $R_{MOM,t}$ is the excess return of the momentum spread in month *t* on either the long leg, the short leg, or the difference. Moreover, RX_t and $CARRY_t$ denote Lustig et. al.'s (2011) dollar and carry risk factors in month *t*, 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 the risk factors are compounded employing Verdelshan's data set (see Table 1 Panel B). The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The columns headed High-Low test the hypothesis in terms of whether the difference of the estimated parameters in the high state minus the estimated parameters in the low state is equal to 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

The table reports risk-adjusted average returns in excess form of 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 1-3) as well as the first principal component, $PC_{C,13}$ to determine the currency RD states. The risk-adjusted average returns in excess form of the MOM(1,1) strategy are the intercept estimates of α_{High} and α_{Low} in the 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, and $R_{MOM,t}$ is the excess return of the momentum spread in month *t*. , RX_t and $CARRY_t$ denote Lustig et. al.'s (2011) dollar and carry risk factors in month *t*, 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 the risk factors are compounded employing Verdelshan's data set (see Table 1 Panel B). The *t*-statistics are based on the heteroskedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The sample period is from 1984:2 to 2010:1.

Measure	$\boldsymbol{\alpha_{High}}$	$\boldsymbol{\alpha_{Low}}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	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 of three different measures of currency return dispersion and the spread between winner and loser portfolio in the formation period. The sample period is from 1984:2 to 2010:1.