The London School of Economics and Political Science

Downside Risk in Stock and Currency Markets

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Declaration

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To Vladimir and Artemiy

Abstract

This thesis consists of an introductory chapter, three main chapters, and a concludingchapter. In Chapter 2, which was nominated for an EFMA 2014 Best Paper Award, I provide a novel risk-based explanation for the profitability of global momentum strategies. I show that the performance of past winners and losers is asymmetric in states of the global market upturns and downturns. Winners have higher downside market betas and lower upside market betas than losers, and hence their risks are more asymmetric. The winner-minus-loser (WML) momentum portfolios are exposed to the downside market risk, but serve as a hedge against the upside market risk. The high returns of the WML portfolios compensate investors for their high risk asymmetry. After controlling for this risk asymmetry, the momentum portfolios do not yield significant abnormal returns, and the momentum factor becomes insignificant in the cross-section. The two-beta CAPM with downside risk explains the cross-section of returns to global momentum portfolios well.

In the third chapter, published in the Review of Finance and the winner of EFMA 2013 John Doukas Best Paper Award, I propose a new factor – the global downside market factor – to explain high returns to carry trades. I show that carry trades have high downside market risk, i.e. they crash systematically in the worst states of the world when the global stock market plunges or when a disaster occurs. The downside market factor explains the returns to currency portfolios sorted by the forward discount better than other factors previously proposed in the literature. GMM estimates of the downside beta premium are similar in the currency and stock markets, statistically significant and close to their theoretical value. I show that the high returns to carry trades are fair compensation for their high downside market risk.

In the fourth chapter, I study whether or not countries' macroeconomic characteristics are systematically related to the downside market risk of their currencies. I find that the downside risk is strongly associated with the local inflation rate, real interest rate and net foreign asset

position. Currencies of countries with higher inflation and real interest rates and lower (negative) net foreign asset position (debtor countries) are more exposed to the downside risk whereas currencies of countries with low inflation and real interest rates and positive net foreign asset position (creditor countries) exhibit 'safe haven' properties. Since inflation and real interest rates determine nominal interest rates which determinecurrency returns which, in turn, determine capital flows and net foreign asset positions, these macroeconomic variables are related. But the local real interest rate has the highest explanatory power in accounting for the cross-section of currency exposure to the downside risk. This suggests that the direction of currency trading is the reason why some currencies are exposed to the downside risk more than others. High currency downside risk is a consequence of investments in high-yield risky currencies and flight from them in 'hard times'. Currencies of low-yield creditor countries, on the contrary, provide a hedge in 'hard times' because capital flies back to them. Currency exposure to the downside market risk has increased significantly in the 2000s when the volume of currency trading by institutional investors increased.

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Chapter 1

Introduction

According to the traditional asset-pricing theory, an asset has high expected returns if its covariance with the stochastic discount factor is high. This theory does not distinguish between good and bad states of the world, between gains and losses. But extensive psychological evidence suggest that investors treat gains and loses differently, and hence, upside and downside risks should have different implications for asset pricing.

In fact, the importance of upside and downside risks was recognized as early as the first theoretical asset-pricing models were developed. Roy (1952) suggests that economic agents care particularly about the downside risk. Markowitz (1959) proposes using semi-variance as a proper measure of risk. Bawa and Lindenberg (1977) provide an extended version of the CAPM where the market beta is separated into the upside beta and the downside beta. Longin and Solnik (2001) consider upside and downside correlations, and Ang and Chen (2001) propose a measure of correlation asymmetry and show that the asymmetric correlation is priced in the US equity market.

There are different reasons that investors may be more averse to losses than they are attracted to gains: behavioral loss aversion in the utility function (Barberis et al., 2001), rational disappointment aversion in the utility function (Gul, 1991), binding short-sale constraints (Chen, Hong and Stein, 2001), wealth constraints (Kyle and Xiong, 2001), funding liquidity constraints and liquidity spirals (Brunnermeier and Pedersen, 2009), fund flow considerations and other reasons. In such settings, assets with higher downside risk relative to their upside risk should have higher expected returns.

Ang et al. (2006) were the first to provide extensive theoretical and empirical evidence on pricing of downside and upside risks. They show how upside and downside risks may be priced cross-sectionally in an equilibrium setting.In a theoretical model with Gul's (1991) disappointment aversion utility function, which down-weights elating (above the certainty equivalent) outcomes relative to disappointing (below the certainty equivalent) outcomes, they show that the traditional market beta 'is not a sufficient statistic to describe the risk-return relationship of an individual stock' because agents are particularly concerned about the downside risk. They show numerically that the traditional CAPM alpha is increasing in the relative downside beta, decreasing in the relative upside beta and, hence, increasing in the downside-upside beta asymmetry. Assets should have higher expected returns if they have higher relative downside betas because such assets perform poorly in bad states of the world when the marginal utility of wealth is high and asset returns are particularly important. Assets with high relative upside betas, on the contrary, do not require a high risk premium, because the marginal utility of wealth is low in such states. Therefore, measures of downside risk have greater explanatory power for describing the cross-section of expected returns.

Ang et al. (2006) also test the validity of their two-beta CAPM in the US stock market. They find that, indeed, the upside and downside risks are priced differently, and that the two-beta CAPM has a much higher explanatory power than the traditional CAPM. Even after controlling for other risk factors (size, book-to-market, momentum, liquidity and volatility), the estimates of the downside risk premium are statistically significant.

This thesis is devoted to the study of downside risk pricing in stock and currency markets. I provide extensive and novel evidence that exposure to downside risk can explain expected returns in these markets better than other risk factors previously proposed in the literature. I show that the anomalous returns to currency carry trade portfolios and momentum portfolios are, in fact, a compensation for their high exposure to the downside market risk.

In parallel to my study, Lettau et al. (2014) provide further evidence on downside risk pricing in stock, currency, commodity and bond markets. Our papers together show that the downside risk is a unifying explanation for returns in different asset markets.

The results of this thesis can be summarized as follows.

Inchapter 2, I provide a novel risk-based explanation for the profitability of global momentum strategies. I show that the performance of past winners and past losers is asymmetric in states of the global market upturns and downturns. Winners have higher downside market betas and lower upside market betas than losers, and hence their upside and downside risks are asymmetric. Greater relative downside risk and lower relative upside risk of past winners are compensated by higher returns. Indeed, such asymmetry in upside and downside market risks explains the returns to the cross-section of global momentum portfolios well.

Although numerous explanations for the momentum anomaly have been put forward, their upside and downside market risks have not been studied thoroughly. DeBondt and Thaler (1987) findthat past winner stocks have greater downside betas than upside betas. Ang et al. (2001) find that the US momentum portfolio has positive and significant loading on a factor that reflects downside risk, and that the downside risk factor explains some of the cross-sectional variation in returns to momentum portfolios. Lettau et al. (2014) consider six US Fama-French size-momentum portfolios and find some evidence that the returns are "broadly positively associated with the downside beta".

Building on these studies, I show that the downside risk alone does not fully explain the returns to the cross-section of momentum portfolios because the upside risk plays a significant role too. In fact, it is the difference in the upside and downside betas (beta asymmetry) which varies across momentum portfolios significantly. For any set of momentum portfolios considered, the asymmetry in betas is monotonically increasing from past losers to past winners. As a result, the winner-minus-loser momentum portfolios are exposed to the downside risk, but hedge against the upside risk.

In the cross-sectional tests, I show that the *relative* downside beta, which captures the *extra* downside risk and, hence, the downside-upside risk asymmetry, explains the returns to the momentum portfolios well, whereas the traditional beta has no explanatory power. The relative downside beta premium is approximately 3-4 percent per month, highly statistically significant and similar in magnitude to the estimates obtained for the stock and currency markets (Lettau et al., 2014; Dobrynskaya, 2014).

In chapter 3, published in the Review of Finance, I propose the global downside market risk factor to explain currency returns. When we examine the downside market risk of carry trade portfolios, we observe a clear risk-return relationship. High interest rate currencies have high and statistically significant downside market risk, which can be measured by the downside beta, the 'disaster beta' or the coskewness[1] with respect to the global stock market return; by contrast, low interest rate currencies have zero downside risk and hence can serve as a hedging instrument. Whereas the consumption betas or traditional market betas of carry trade long-short portfolios are rather small, the downside market betas are several times higher and statistically significant, especially if we measure them in the worst states of the world (e.g., when there is a market crash or a disaster event).

I show that the spread in the downside market betas and the coskewness across currency portfolios sorted by interest rate is sufficient to justify the spread in their returns. The GMM estimates of the downside beta and coskewness premiums in the currency market are highly significant. Moreover, the estimation of the downside beta or coskewness CAPM for currency and stock portfolios *jointly* produces a good fit of the model, whereas the traditional CAPM is rejected on several grounds. The downside risk has much higher explanatory power for the cross-section of returns in both markets, and the downside risk premiums are similar in both markets and are close to the theoretical values. In fact, I cannot reject the hypothesis that the downside risk is priced similarly in the currency and stock markets. I conclude that the high excess returns to carry trades are not a free lunch but rather fair compensation for their high downside market risk.

[1] Coskewness is measured as beta with respect to the market volatility, R_m^2.

In chapter 4, I study whether or not there is a systematic relationship between currency exposure to the downside market risk and macroeconomic characteristics of the respective countries. I try to answer the question as to which currencies tend to crash when the stock market goes down and which currencies serve as a 'safe haven'. Although in chapter 3 I show that the level of the nominal interest rate is strongly associated with currency downside risk, the nominal interest rate is not necessarily the only and best determinant of currency exposure to the downside risk.

The main findings of chapter 4 can be summarized as follows. Firstly, currencies systematically differ in terms of their exposure to the downside risk indeed and the spread in the downside betas of currencies is high and significant. Moreover, currency exposure to the downside risk has increased dramatically since the beginning of the 21st century in parallel with the growing volume of currency trading.

Secondly, currency downside betas are strongly associated with particular levels of three out of eight macroeconomic variables considered: the inflation rate, the real interest rate and the net foreign asset position. Countries with high inflation rates, high real interest rates and low (negative) net foreign assets have currencies with high exposure to the downside risk whereas countries with the opposite characteristics have currencies with 'safe haven' properties.

These three macroeconomic variables are, in fact, related, because higher inflation and higher real interest rates in an economy lead to higher nominal interest rates and higher nominal currency returns, which, in turn, lead to higher capital inflows and lower net foreign assets. The high explanatory power of these variables for the downside risk suggests that the direction of currency trading is the reason why some currencies are exposed to the downside risk more than others. Currencies of debtor countries with high returns (investment currencies) have higher exposure to the downside risk because capital is withdrawn in bad times. Currencies of creditor countries with low returns (funding currencies) provide a hedge in bad times because capital flies back to them.

In a multivariate setting, when inflation and/or real interest rates are controlled for, the net foreign asset position becomes an insignificant determinant of currency downside risk. Whereas the real interest rate has the highest explanatory power in the recent ‘post-euro’ period, the inflation rate was a better determinant of currency risk in the 90s. I do not find evidence, that other macroeconomic variables, previously suggested in the literature, are systematically related to currency risk.

My findings shed some light on why a carry trade is a very risky investment strategy. Since nominal interest rates can be high due to high real interest rates, high inflation rates or both, I decompose nominal interest rates into inflation and real interest rates and form double-sorted currency portfolios. I show that currencies with the same level of real interest rates but different inflation rates have the same downside risk, whereas, controlling for inflation, currencies with higher real interest rates have a higher downside risk. Therefore, the high downside risk of carry trades turns out to be a consequence of high real interest rates in the investment countries and low real interest rates in the funding countries, rather than the nominal interest rates. When nominal and real interest rates correlate significantly (e.g. in developed countries), high levels of these rates in an economy are both associated with high downside risk of its currency, but when the correlation between these rates is low, the real interest rate has the highest explanatory power for currency exposure to the downside risk.

Overall, the results of this thesis suggest that we should pay greater attention to an asset’s downside risk because it is a more relevant measure of risk than the overall market risk and it carries an extra return premium in different asset markets.

Chapter 2

Asymmetric Risks of Global Momentum Strategies

2.1.INTRODUCTION

Since Jegadeesh and Titman (1993), the momentum anomaly has received a lot of attention. Buying past winners and selling past losers generates abnormal returns in the short run, which cannot be explained by conventional risk measures (e.g. the standard deviation and the market beta) and provide evidence for market inefficiency. Momentum strategies proved to be profitable around the world, at the level of national equity indices (e.g. Asness, Liew, and Stevens, 1997; Richards, 1997; Cenedese et al., 2013) and at the individual stock level (Rouwenhorst, 1998, 1999), among currencies (Okunev and White, 2003; Menkhoff et al., 2012), commodities, bonds and other assets (Gorton et al., 2008; Asness, Moskowitz, and Pedersen, 2013).

In this chapter, I provide a novel risk-based explanation for the profitability of global momentum strategies. I show that the performance of past winners and past losers is asymmetric in states of the global market upturns and downturns. Winners have higher downside market betas and lower upside market betas than losers, and hence their upside and downside risks are asymmetric. Greater relative downside risk and lower relative upside risk of past winners are compensated by higher returns. Indeed, such asymmetry in upside and downside market risks explains the returns to the cross-section of global momentum portfolios well.

The importance of separating the overall market risk into the upside and downside risks for asset pricing was recognized in early papers (e.g. Roy, 1952; Markowitz, 1959; Bawa and Lindenberg, 1977) and was articulated in Ang and Chen (2002) and Ang et al. (2006) for the US stock market. More recently, Lettau et al. (2014) and Dobrynskaya (2014) provide further convincing evidence that the models with downside risk (e.g. two-beta CAPM) have greater explanatory power in the stock, currency, commodity and bond markets. They show that the downside risk is a unifying explanation for returns in different asset markets.

Although numerous explanations for the momentum anomaly have been put forward, their upside and downside market risks has not been studied thoroughly. DeBondt and Thaler (1987) findthat past winner stocks have greater downside betas than upside betas. Ang et al. (2001) find that the US momentum portfolio has positive and significant loading on a factor that reflects downside risk, and that the downside risk factor explains some of the cross-sectional variation in returns to momentum portfolios. Lettau et al. (2014) consider six US Fama-French size-momentum portfolios and find some evidence that the returns are “broadly positively associated with the downside beta”.

Building on these studies, I show that the downside risk alone does not fully explain the returns to the cross-section of momentum portfolios because the upside risk plays a significant role too. In fact, it is the difference in the upside and downside betas (beta asymmetry) which varies across momentum portfolios significantly. For any set of momentum portfolios considered, the asymmetry in betas is monotonically increasing from past losers to past winners. As a result, the winner-minus-loser momentum portfolios are exposed to the downside risk, but hedge against the upside risk[2].

In the cross-sectional tests, I show that the *relative* downside beta, which captures the *extra* downside risk and, hence, the downside-upside risk asymmetry, explains the returns to the momentum portfolios well, whereas the traditional beta has no explanatory power. The relative downside beta premium is approximately 3-4 percent per month, highly statistically significant and similar in magnitude to the estimates obtained for the stock and currency markets (Lettau et al., 2014; Dobrynskaya, 2014).

[2] The finding that the momentum portfolios perform badly in states of global market upturns goes in line with Daniel and Moskowitz (2013), who show that momentum portfolios crash when the market rebounds after a market decline, and when the market return is high.

My findings are similar no matter which set of momentum portfolios I consider. I study the US, global and regional momentum portfolios of individual stocks, global momentum portfolios of country indices, currency momentum portfolios and US short-term and long-term equity reversal portfolios. I show that momentum is a global phenomenon indeed, and its upside-downside risk structure is similar around the world and in different asset markets. Hence, the upside-downside risk asymmetry can be considered a unifying explanation of returns to momentum portfolios in various markets. The results are robust to different estimation methodologies (Fama-MacBeth, 1973, and Hansen's GMM, 1982) and different periods of study.

The rest of the paper is organized as follows. In section 2.2, I describe the theoretical asset pricing models with downside risk to motivate my risk measures. Section 2.3 is devoted to the data description and portfolio formation. In section 2.4, I present the portfolio statistics and the results of the cross-sectional tests for different sets of momentum and reversal portfolios. Section 2.5 is devoted to robustness tests. Section 2.6 concludes the paper.

2.2.CAPM WITH UPSIDE AND DOWNSIDE RISKS

The importance of upside and downside risks was recognized as early as the first theoretical asset-pricing models were developed. Roy (1952) suggests that economic agents care particularly about the downside risk. Markowitz (1959) proposes using semi-variance as a proper measure of risk. Bawa and Lindenberg (1977) provide an extended version of the CAPM where the market beta is separated into the upside beta and the downside beta. Longin and Solnik (2001) consider upside and downside correlations, and Ang and Chen (2001) propose a measure of correlation asymmetry and show that the asymmetric correlation is priced in the US equity market.

Ang et al. (2006) show how upside and downside risks may be priced cross-sectionally in an equilibrium setting. In a theoretical model with disappointment aversion, they show numerically that the traditional CAPM alpha is increasing in the relative downside beta, decreasing in the relative upside beta and, hence, increasing in the downside-upside beta asymmetry. Assets should have higher expected returns if they have higher relative downside betas because such assets perform poorly in bad states of the world when the marginal utility of wealth is high and asset returns are particularly important. Assets with high relative upside betas, on the contrary, do not require a high risk premium, because the marginal utility of wealth is low in such states.

Ang et al. (2006) test the validity of the two-beta CAPM in the US stock market. They find that, indeed, the upside and downside risks are priced differently, and that the two-beta CAPM has a much higher explanatory power than the traditional CAPM. Even after controlling for other risk factors (size, book-to-market, momentum, liquidity and volatility), the estimates of the downside risk premium are statistically significant.

More recently, asset pricing models with downside market risk proved to be as successful in explaining returns in the currency, commodity and bond markets (Lettau et al, 2014; Dobrynskaya, 2014), as in the equity market. The downside risk is shown to be priced similarly in different asset markets and different geographical markets.

2.3.DATA AND PORTFOLIO FORMATION

I consider a variety of momentum and reversal portfolios around the globe to show that the upside-downside risk asymmetry is a universal phenomenon.

Firstly, I consider 10 US equal-weighted and value-weighted momentum portfolios, which are formed by sorting NYSE, AMEX and NASDAQ stocks in month t by their total returns in months t-12 to t-2. The month prior to the sort date is excluded because of the short-term reversal. Portfolio 1 (low) is the past-loser portfolio, and portfolio 10 (high) is the past winner portfolio. I also construct the winner-minus-loser (WML) portfolios which have a long position in portfolio 10 and a short position in portfolio 1. The longest time series of data is available for these portfolios: from January 1927 until July 2013. The data is taken from the Fama-French data library.

Secondly, I consider global and regional momentum portfolios of *individual stocks*. These portfolios are formed by monthly sorts of stocks in the corresponding region by their previous-year (t-12 to t-2) performance. The data on these portfolios is also obtained from the Fama-French data library and covers the period from November 1990 until August 2013. I collect the raw data on 25 equal-weighted Global, European, Asian-Pacific, Japanese and North-American size-momentum portfolios and construct 5 momentum portfolios and 5-1 WML portfolio for each region. The Global portfolios consist of stocks from 23 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, Sweden, the UK, and the USA; the European portfolios consist of stocks from 16 countries; the Asian-Pacific portfolios consist of stocks from 4 countries; and the North-American portfolios consist of stocks from Canada and the USA.

The third set of momentum portfolios is formed by double sorts of individual stocks by their previous year performance and the market capitalization. I consider global 25 size-momentum portfolios form the Fama-French data library.

The fourth set of global momentum portfolios is formed by sorting *country indices* in month t by their total returns in US dollars in months t-12 to t-2. The portfolios are rebalanced every month. Following Richards (1997) and Cenedese et al. (2013), I use MSCI country indices as the base assets. These indices often represent a benchmark for country index ETFs, and hence they are traded assets which can be used to form such momentum portfolios in practice. There are 40 countries in the sample: Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, South Korea, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, South

Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the UK, and the USA. The sample period is from January 1983 until August 2013, the first sort is done in December 1983 and the first return is measured in January 1984. For 20 countries, the indices are available for the whole period, 12 indices start in December 1987, 4 indices start in December 1992 and 4 indices start in December 1994. I form 6 equally-weighted portfolios of indices, where portfolio 1 represents past loser countries and portfolio 6 represents past winner countries. Once new indices appear, they enter the portfolios a year later, and the portfolios become more diversified. I also form the 6-1 WML portfolio which represents a global momentum strategy.

The fifth set consists of 5 *currency* momentum portfolios which are formed by sorting currencies in month t by their exchange rate appreciation relative to the US dollar during the period t-12 to t-2 and held for 1 month. The sample consists of 45 currencies, but the actual number of currencies varies from 10 (November 1984) to 41 (December 1998) due to data limitations and creation of the Euro zone. The exchange rate data cover the period from October 1983 until August 2013, the first sort is done in October 1984 and the first portfolio returns are measured in November 1984. The end-of-month exchange rate data are collected from various data sources via Datastream.

I also consider short-term and long-term reversal portfolios of US stocks for the periods January 1927 - July 2013 and January 1931 – July 2013, respectively. The short-term reversal portfolios are sorted by the performance in the previous month, whereas the long-term reversal portfolios are sorted by the performance in the previous five-year period. All portfolios are rebalanced monthly. The data is taken from the Fama-French data library.

I use the following risk factors in the analysis: the market factor (the US market index for the US portfolios and the developed countries World MSCI index for the global and regional portfolios), the market volatility factor (the squared market factor), the momentum factor (the Fama-French US momentum factor before November 1990, the Fama-French global momentum factor afterwards, which is formed by sorting individual stocks in 23 countries by their trailing previous-year performance), and the global size factor (the Fama-French global SMB factor).

2.4.RESULTS

2.4.1. US MOMENTUM PORTFOLIOS

I start the analysis of US momentum portfolios because the longest time series of data is available for these portfolios. Table 2.1 reports the return and risk characteristics of 10 value-weighted and 10 equal-weighted momentum portfolios, as well as the WML zero-cost portfolios.

The momentum effect is strong in the US; the zero-cost value-weighted (equal-weighted) momentum strategy generated an average return of 14.27 (9.80) percent per annum during 1927-2013. Past-winner portfolios generally have lower return standard deviation, skewness, kurtosis and market beta than past loser portfolios, but higher returns. Therefore, the WML portfolios generate high and virtually risk-free returns, if these measures of risk are considered. This represents the well-known momentum anomaly.

Keeping the Ang et al. (2006) two-beta CAPM in mind, I estimate the upside and downside market betas of the momentum portfolios in the following time-series regression:

$$r_{it} = \alpha_i + \beta_i^- * r_{Mt} + \gamma_i * r_{Mt} * D_t + \varepsilon_{it}, \qquad (2.1)$$

where $D_t = \begin{cases} 0, r_{Mt} \leq 0 \\ 1, r_{Mt} > 0 \end{cases}$, r_{it} is the return on portfolio *i*, r_{Mt} is the US market return, β_i^- is the estimate of the downside beta[3], γ_i is the estimate of the upside-downside beta asymmetry, $\beta_i^+ = \beta_i^- + \gamma_i$ is the upside beta and ε_{it} is the error term. Then, the relative downside beta is $(\beta_i^- - \beta_i)$, and the relative upside beta is $(\beta_i^+ - \beta_i)$, where β_i is the traditional beta,

[3] As defined here, the downside beta is conditional on the negative market return. Another way to define downside beta is to condition on the episodes when the market return is below its mean. This alternative specification produces similar results and it is not reported.

estimated in the regression of portfolio return on the market return. This approach to estimate the upside and downside betas jointly is superior to the one, used in Lettau et al. (2014), because no information regarding the upside is lost[4]. The relative downside beta measures *additional* market risk on the downside, after controlling for the overall market risk (the traditional market beta). A portfolio may have lower market beta, but greater exposure to the downside risk, and hence may require higher returns, because investors care more about performance in downstates. This can only be seen after separating the overall market risk and the downside market risk.

Table 2.1 reports the relative downside betas, the relative upside betas and the beta asymmetry $\left(\beta_i^- - \beta_i^+ = -\gamma_i\right)$ of the US momentum portfolios. We observe a striking increasing pattern for the relative downside betas and decreasing pattern for the relative upside betas along the portfolio rank. Past winner portfolios have higher downside risk and lower upside risk than past loser portfolios. Therefore, the WML portfolios are exposed to the downside risk, but hedge against the upside risk. Since the downside risk is more important for an investor, the WML portfolios require risk premiums.

Because both the relative downside betas and the relative upside betas are different for past winners and past losers, there is an even stronger positive relationship between the beta asymmetry and portfolio rank. Past losers have higher upside betas than downside betas, whereas past winners have higher downside betas than upside betas. The beta asymmetry ranges from -0.71 to 0.99 and it is statistically significant for several top and bottom portfolios, as well as the WML portfolios. The results are similar in cases of value-weighted and equal-weighted portfolios.

Figure 2.1 illustrates the relationships between the relative upside betas, relative downside betas, beta asymmetry and portfolio rank (for the value-weighted portfolios). We observe clear monotonic relationships.

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[4]Lettau et al. (2014) just pick the downside episodes and estimate the downside beta in that sub-sample.

The differences in the upside and downside risks of momentum portfolios can explain the differences in their returns. Figure 2.2 plots the predicted versus realized returns of US momentum portfolios, where the predictions are made by the traditional CAPM (left-hand-side) and the two-beta CAPM (right-hand side). Indeed, the two-beta CAPM has very high explanatory power (R^2 of 0.93 and 0.94), whereas the traditional CAPM performs worse (R^2 of 0.46 and 0.66), and the beta premium is even negative.

I use the following specification of the two-beta CAPM for the cross-sectional regressions:

$$r_i - r_f = \beta_i \lambda + \left(\beta_i^- - \beta_i\right)\lambda^- + \mu + \varepsilon_i, \qquad (2.2)$$

where λ is the traditional beta premium, λ^- is the extra downside beta premium, and μ is the common pricing error, which can be restricted to zero[5]. This specification nests the traditional CAPM if the extra downside risk is not priced or if the downside beta is equal to the traditional beta (and, hence, to the upside beta). This specification of the two-beta CAPM (called downside-risk CAPM) was estimated in Lettau et al. (2014) for different asset classes, and it is alternative to the specification of Ang et al. (2006):

$$r_i - r_f = \beta_i^+ \lambda^+ + \beta_i^- \lambda^- + \mu + \varepsilon_i, \qquad (2.3)$$

where λ^+ is the upside beta premium and λ^- is the downside beta premium. Since the traditional beta is a weighted average of the upside beta and the downside beta, we need to have any two betas of the three to fully specify the model. If the *relative* downside beta premium is positive, it means that the *relative* upside beta premium is negative. Specification (2) is more convenient because we can easily compare it with the traditional CAPM specification and see the contribution of the relative downside risk.

Table 2.2 reports the estimates of risk premiums in the cross-sectional tests of the traditional CAPM and the downside-risk CAPM (DR-CAPM) with and without the constant. I

[5] It is common in the recent literature to restrict the pricing error to zero (e.g. Burnside et al., 2011; Lustig et al., 2011; Cenedese et al., 2013).

employ two alternative methodologies to estimate risk premiums: the Fama-MacBeth (1973) and Hansen's (1982) two-step GMM. In the latter, the factor betas and risk premiums are estimated jointly, and the standard errors are corrected to account for the generated regressor problem. I use the identity weighting matrix in the first step, and then re-optimize using the efficient weighting matrix. The moment conditions are specified as in Cochrane (2005):

$$\begin{cases} E(r_{jt} - \alpha_j - b_j f_t) = 0 \\ E(r_{jt} - \alpha_j - b_j f_t) \otimes f_t = 0 \quad (2.4) \\ E(r_{jt} - b_j \lambda - \mu) = 0 \end{cases}$$

where f_t is either a risk factor or a vector of factors, r_{jt} is the excess return on portfolio j, b_j is a factor beta, and λ is a factor risk premium. The first two moments estimate factor betas, and the third moment estimates factor risk premiums.

The traditional CAPM has negative R^2 in case of no constant, and negative beta premiums, significant intercepts and low R^2 in case with a constant. It is also rejected by the test for the over-identifying restrictions (J-statistics). Therefore, the traditional CAPM cannot explain the returns to the momentum portfolios. The downside-risk CAPM, on the contrary, performs very well in terms of both R^2 and J-statistics. The relative downside beta premium is about 2 percent per month and it is highly significant irrespective of the estimation methodology[6]. The same magnitude of the downside risk premium was also obtained in Dobrynskaya (2014) for equity and carry trade portfolios. In case with a constant, the traditional beta premium and the constant are insignificant, so that the full explanatory power of the model comes from the downside risk component. The high momentum return is a compensation for its high relative downside risk and high downside-upside risk asymmetry.

My results differ from Lettau et al.'s (2014) results who do not find such a strong support for the downside-risk CAPM in the cross-section of six US size-momentum

[6] In an alternative specification of the two-beta CAPM with relative upside betas instead of the relative downside betas, the relative upside beta premium is negative and the explanatory power of the model is exactly the same by construction. These results are not reported because they are redundant.

portfolios, although they write that the returns are "broadly positively associated with the downside beta". The reason is that they look at the downside betas instead of *relative* downside betas which measure downside-upside beta asymmetry. It turns out that the downside betas of these portfolios are similar and, hence, they cannot explain the differences in these portfolio returns. But the relative downside betas, relative upside betas and the downside-upside-beta asymmetry vary across the portfolios significantly and are well aligned with the portfolio returns. Neglecting the upside component leads to misinterpretation of the results. I confirm the validity of the downside-risk CAPM for the cross-section of 25 global size-momentum portfolios in section 2.4.3.

2.4.2. GLOBAL AND REGIONAL MOMENTUM PORTFOLIOS OF STOCKS

In this section, I consider global and regional momentum portfolios of individual stocks and show that the downside-upside risk asymmetry of momentum returns is a global phenomenon. Table 2.3 reports the returns and risks of 5 global, 5 European, 5 Asian-Pacific and 5 North-American momentum portfolios and the corresponding 5-1 WML portfolios. The momentum strategies are profitable in all regions with the highest momentum return in Europe (17.58 percent pa) and the lowest momentum return in the Asian-Pacific region (6.55 percent pa)[7].

In all regions, the high returns to the WML portfolios cannot be explained by the market factor because their global market betas are negative in all cases, as in Fama and French (2012). While the market betas are somewhat decreasing with the portfolio rank, the relative downside betas are monotonically increasing and the relative upside betas are monotonically decreasing. The past winner portfolios have greater exposure to the downside risk and lower exposure to the upside risk than the past loser portfolios. Consequently, the winner portfolios exhibit a greater degree of the downside-upside risk asymmetry (β^{-}-β^{+}). This asymmetry is

[7] The exception is Japan where the WML portfolio is unprofitable (as in Fama and French, 2012), and its upside and downside betas do not differ significantly too. The results for the Japanese momentum portfolios are not reported.

statistically significant for the winner and WML portfolios in all regions. In general, the global and regional momentum portfolios have similar risk structure as the US momentum portfolios despite the different base assets and different sample periods.

As in the US case, the two-beta CAPM has a high explanatory power in the cross-section of momentum portfolios in all regions (figure 2.3). The predicted returns are very close to the realized returns with R^2 of 77-96 percent.

Table 2.4 reports the Fama-MacBeth (1973) and Hansen's (1982) GMM estimates of risk premiums in the CAPM and DR-CAPM specifications. In case of the CAPM, the beta premium is negative and insignificant, the intercept is highly significant, the adjusted R^2 is negative in most cases and the model is rejected by the J-statistics in case with a constant. As in case of the US, the traditional market factor alone cannot explain the returns to the global momentum portfolios. When the relative downside risk is also taken into account, the beta premiums become positive but insignificant, the intercepts become insignificant, and the relative downside beta premiums are highly significant in all cases. The DR-CAPM is never rejected by the J-statistics. The DR-CAPM has high explanatory power for all sets of momentum portfolios, and this explanatory power comes solely from the downside risk component which captures the downside-upside risk asymmetry.

2.4.3. GLOBAL SIZE-MOMENTUM PORTFOLIOS

Table 2.5 reports the returns, downside and upside betas and the beta asymmetry of 25 global size-momentum double-sorted portfolios. The portfolio average returns are decreasing with size and increasing with past returns. As a result, all SMB and WML long-short portfolios generate positive returns. The momentum strategy is profitable for all size quintiles, and the momentum effect is stronger for small firms.

The relative downside betas are decreasing with size and increasing with past returns. The relative upside betas, on the contrary, are increasing with size and decreasing with past returns. Small winner stocks have the highest downside risk, the lowest upside risk and the greatest downside-upside risk asymmetry. Big loser stocks have the lowest downside risk, the highest upside risk and the lowest (negative) risk asymmetry. The WML portfolios have positive and statistically significant beta asymmetry for all size quintiles. The SMB portfolios have positive, but insignificant, beta asymmetry. Therefore, this risk asymmetry does not fully explain the size anomaly.

In figure 2.4, I plot predicted versus realized returns of the 25 global size-momentum portfolios where the predictions are made by the traditional CAPM, the three-factor CAPM with the market, size and momentum factors, and the two-beta CAPM. The traditional CAPM has low explanatory power (R^2 is 0.35), and the market risk premium is negative. The three-factor CAPM explains the returns much better (R^2 is 0.70), but this result is not surprising because the size and momentum factors are derived from these portfolios themselves. The two-beta CAPM has an even higher explanatory power despite the lower number of factors (R^2 is 0.75). The asymmetry in betas is aligned well with the portfolio returns.

Table 2.6 reports the Fama-MacBeth risk premiums in alternative multifactor specifications. In the CAPM (column (1)), the beta premium is negative and the intercept is highly statistically significant. In the DR-CAPM (column (2)), only the relative downside beta premium is significant. This model outperforms the three-factor model (column (3)), where the beta premium is negative and the intercept is significant again. When all risk factors are included (column (4)), the downside risk factor has the highest statistical significance, although the size and momentum factors are significant too. Only the traditional beta is dead.

2.4.4. GLOBAL MOMENTUM PORTFOLIOS OF COUNTRY INDICES

In this section, I consider alternative set of global momentum portfolios, which are formed by sorting country indices instead of individual stocks. Country indices also exhibit momentum, and the WML portfolio of country indices generates high returns which cannot be explained by conventional risk factors (e.g. Richards, 1997; Cenedese et al., 2013).

Table 2.7 reports the return and risk characteristics of 6 momentum portfolios of country indices and the 6-1 WML portfolio. Both the returns in the local currencies and the returns in the US dollars are increasing with the portfolio rank. According to the Uncovered Equity Parity (Hau and Rey, 2006), equity return differential in the domestic currency should be offset by the depreciation of the domestic currency, but this is clearly not the case. Winner portfolios consistently generate higher exchange-rate adjusted returns in excess of the US returns, whereas loser portfolios generate negative excess returns (row 4 in table 2.7). This violation of the UEP has been documented in Cenedese et al. (2013), and it leads to the global momentum strategies being profitable. Such global momentum strategy WML had an average USD return of about 13 percent per annum in 1984-2013.

The profitability of this momentum strategy cannot be explained by conventional risk measures, like the standard deviation, skewness or market beta because all of them are similar for the 6 portfolios considered. As a result, the WML portfolio has no market risk and low volatility.

As in the previous sections, portfolios with higher rank have higher relative downside betas and lower relative upside betas. Whereas the loser portfolios 1 and 2 have symmetric upside and downside risks, the difference between the downside and upside betas is monotonically increasing with the portfolio rank and it is statistically significant for portfolios 3-6 and the WML portfolio. As a results, although the WML portfolio has the traditional beta of almost zero, it has a positive relative downside beta, a negative relative upside beta and a high beta asymmetry.

The last row of table 2.7 shows how the index momentum portfolios load on the Fama-French global momentum factor, which is formed by sorting individual stocks[8]. The loadings

[8] The momentum beta is estimated in a two-factor beta-momentum specification.

monotonically increase with the portfolio rank and are highly statistically significant for the loser and winner portfolios. The index-level momentum portfolios and the stock-level momentum portfolios have a similar risk structure and a similar exposure to downside and upside market risks.

Figure 2.5 plots realized versus predicted returns of the 6 momentum portfolios of country indices, where the predicted returns are estimated using the traditional CAPM and the two-beta CAPM. The CAPM does not explain the returns to the momentum portfolios at all because the CAPM betas and, hence, predicted returns of all portfolios are similar while the realized returns differ significantly. The two-beta CAPM, on the contrary, predicts the returns very well with R^2 of 0.91.

Table 2.8 reports the risk premiums in cross-sectional regressions. As before, the DR-CAPM has a much higher explanatory power than the CAPM, the relative downside beta premium is highly significant whereas the traditional beta premium is not. The estimates of the downside risk premium are similar to the estimates obtained for the global portfolios of individual stocks. Once again, we see that the downside-upside risk asymmetry of momentum portfolios is a global phenomenon and it is priced similarly around the world. It is crucial to account for this asymmetry to fully understand risks of momentum strategies.

2.4.5. CURRENCY MOMENTUM PORTFOLIOS

In addition to various equity momentum strategies, I consider currency momentum strategies as an out-of-sample test.A recent comprehensive study of currency momentum strategies by Menkhoff et al. (2012) provides strong evidence that currency momentum strategies are profitable, particularly for short holding periods (1 month), and the profits are mostly generated by the momentum in spot exchange rates rather than in forward discounts. The authors show that the currency momentum returns cannot be fully explained by transaction costs, business cycle risk, liquidity and volatility risks and other traditional risk factors, used in equity and currency literature. They conclude that although the FX markets are more liquid and efficient than the stock markets, “the properties of momentum strategies are fairly similar, which suggests that momentum profits in different asset classes could share a common root”.

To be consistent with my previous analysis of the equity market, I consider a currency momentum strategy with 11-month formation period and 1-month holding period. This strategy is one of the most profitable strategies out of 50 strategies considered in Menkhoff et al. (2012). Its average annual return was 6 and 7.6 percent in 1976-2010, depending on whether the spot rate changes or the total excess returns (including the interest rate differentials, or the forward discounts) were used to sort currencies into portfolios and to measure the subsequent returns. Since the spot rate changes exhibit greater momentum, I form 5 momentum portfolios by sorting currencies by their preceding spot rate appreciation relative to the US dollar. The winner portfolio includes 1/5 of currencies that have appreciated mostly and the loser portfolio includes 1/5 of currencies that have depreciated mostly.

Panel A of table 2.9 reports the returns and risk characteristics of the 5 currency momentum portfolios and the WML portfolio. Indeed, the average portfolio return is increasing with the portfolio rank, and the WML portfolio generated a return of 7.82 percent per annum during 1984-2013. This return is lower compared to the stock market, but still significant and it cannot be explained by the traditional risk measures such as standard deviation, skewness or the market beta.

The relative downside and upside betas exhibit similar patterns as in the stock market. The loser portfolio has the lowest relative downside beta and the highest relative upside beta whereas the winner portfolio has the highest relative downside beta and the lowest relative upside beta. The asymmetry in betas increases with the portfolio rank and it is high and statistically significant for the WML portfolio.

The last row in panel A shows how the currency momentum portfolios load on the global equity momentum factor. Although the loadings are not very high, they have predictable signs and are statistically significant for the winner, loser and WML portfolios. Therefore, momentum portfolios in different asset markets have a common component. My findings suggest that the relative downside risk can explain this common component because all momentum portfolios have similar exposure to the downside risk.

Panel B of table 2.9 shows the Fama-MacBeth and the efficient GMM risk premiums in the cross-sectional regressions. Since the intercepts are insignificant in all specifications, they are dropped out. As before, the traditional CAPM has low explanatory power and the beta premium is negative. The DR-CAPM has higher explanatory power, which comes predominantly from the downside-risk component. The estimates of the relative downside beta premium are all statistically significant and similar in magnitude to the estimates obtained for the stock market.

2.4.6. ALL MOMENTUM PORTFOLIOS TOGETHER

In this section, I show that the asymmetric exposure to the downside and upside market risks is a unifying explanation of returns to momentum portfolios in different markets. I analyze all portfolios studied previously as a single cross-section. I have 48 portfolios in total: 10 US portfolios, 5 global, 5 European, 5 Asian-Pacific and 5 North-American portfolios of stocks, 6 global portfolios of country indices, 5 currency portfolios and 7 corresponding WML portfolios. The sample period is restricted November 1990 – August 2013 since some portfolios are not available prior to that period.

The correlation matrix for returns of the 7 WML portfolios is presented in table 2.10. Generally, all portfolios have positive and statistically significant correlations with each other, but the correlation coefficient vary. The highest correlations are observed between portfolios of individual stocks (up to 0.9), and the lowest correlation are observed for the portfolios of country indices and currencies (0.15-0.3). Therefore, global momentum portfolios perform differently over time despite the similarities in their relative upside and downside betas.

In figure 2.6, I plot predicted and realized returns of the 48 momentum portfolios. In the left-hand-side figure, the predictions are made by the CAPM. There are three clear clusters of momentum portfolios. The 7 portfolios in the oval cluster are the WML portfolios. The 5 portfolios in the rhombus cluster are the currency portfolios. The portfolios in the right-angle cluster are equity portfolios of stocks and country indices. Within each cluster, all predicted returns are similar whereas the actual returns vary significantly. The CAPM is not able to explain the momentum portfolio returns.

When the DR-CAPM is used to predict returns (the right-hand-side figure), all portfolios are scattered around the 45-degree line with R^2 of 57%. The currency portfolios are closer to the origin and the equity portfolios are further from it. But there are no visible clusters, and all WML portfolios are close to the 45-degree line. Therefore, the DR-CAPM has a high explanatory power for the single cross-section of 48 momentum portfolio.

Table 2.11 reports the Fama-MacBeth estimates of cross-sectional regressions with alternative specifications. The traditional CAPM is rejected because the market risk premium is statistically insignificant in case with a constant and the R^2 is negative in case of no constant. When the market and momentum factors are included (column (3)), both are significant, the intercept becomes insignificant, and the adjusted R^2 increases from 16 to 49 percent. Therefore, inclusion of the momentum risk factor improves the explanatory power of the CAPM dramatically.

The DR-CAPM has an even higher adjusted R^2, and the both premiums are statistically significant, whereas the intercept is not[9]. The relative downside beta premium is 3-4 percent per month which can be considered a unifying estimate across different markets around the world. Most importantly, inclusion of the momentum factor (column (5)) does not improve the explanatory power of the DR-CAPM, and the momentum factor itself is statistically

[9] The intercepts in specifications (3)-(5) are statistically insignificant and can easily be dropped out without affecting the results.

insignificant. After controlling for the downside-upside risk asymmetry, the momentum factor becomes redundant.

2.4.7. US REVERSAL PORTFOLIOS

As an extension, I analyze reversal portfolios which have also been shown to generate abnormal returns. I consider short-term and long-term reversal portfolios of US individual stocks. The short-term reversal portfolios are sorted by the previous month return and held for one month. The long-term reversal portfolios are sorted by the previous five-year return and held for one month.

There is a strong short-term and a moderate long-term reversal effect. Stocks which had higher prior return perform worse in the subsequent month. The loser-minus-winner one-month reversal portfolio had an average return of 19 percent per annum during 1984-2013. The loser-minus-winner five-year reversal portfolio generated an average return of 6 percent per annum during the same period.

Figures 2.7 and 2.8 plot the predicted versus realized returns of the short-term and long-term reversal portfolios, respectively. In the left panels, the prediction is made by the traditional CAPM, whereas the two-beta CAPM is used in the right panels. As in the case of momentum portfolios, the traditional CAPM has weak or no explanatory power for the cross-section of reversal portfolios. But the two-beta CAPM performs well again (the $R^2$is between 58 and 80 percent).

In the cross-sectional tests (table 2.12), the relative downside beta premium is lower in magnitude than in the case of momentum portfolios, but still statistically significant. In case of short-term reversal, the beta premium is also significant. In case of long-term reversal, only the downside risk premium is weakly significant. The downside-upside risk asymmetry explains the returns to the reversal portfolios as well. The past loser portfolios generally have higher relative downside betas and lower relative upside betas (greater beta asymmetry) than past winner portfolios and require risk premiums.

2.5. ROBUSTNESS TEST: RISKS OF MOMENTUM PORTFOLIOS IN SUB-PERIODS

As a robustness check, I study whether the asymmetry in the upside and downside betas of momentum portfolios was persistently observed in different periods of time. I consider the US momentum portfolios of individual stocks for which the longest time series of data is available. Firstly, I split the whole time period into two equal sub-periods 1927-1969 and 1970-2013 and calculate the return and risk characteristics of the momentum portfolios in theses sub-periods. Secondly, I consider a more recent period 2000-2013 separately. This period is characterized by high volume of trade by institutional investors.

Table 2.13 reports the returns and betas of the momentum portfolios in the three sub-periods. The momentum strategy was always profitable, although the average WML return is much lower in 2000-2013. The reason is the crash in momentum profits during the recent financial crisis.

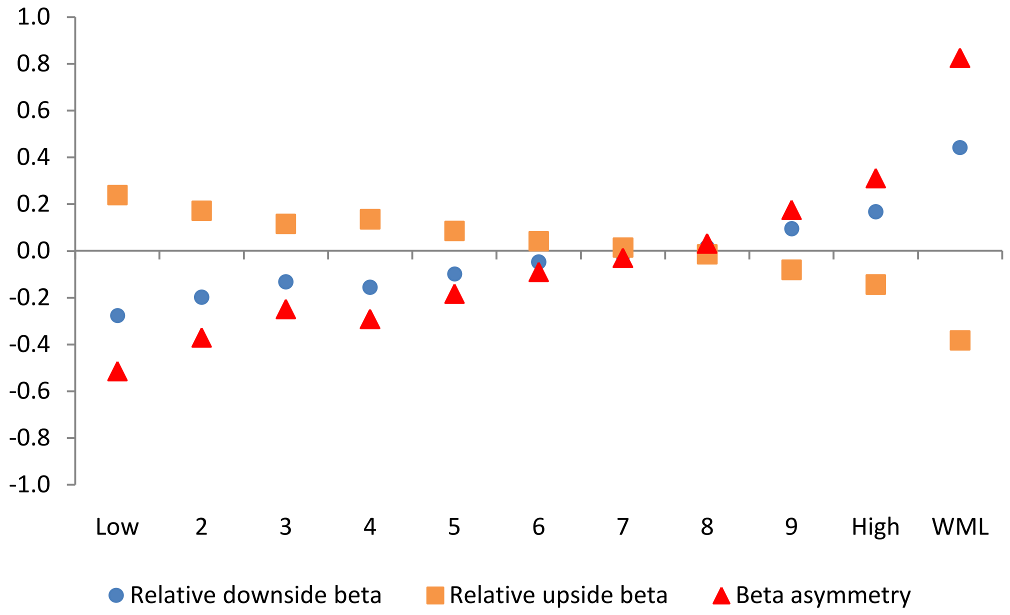
The market betas of the past loser portfolios were always higher than those of the past winner portfolios. Therefore, the market betas cannot explain the high returns to the WML portfolio in any period. The relative downside betas and the beta asymmetry, on the contrary, were always increasing with the portfolio rank. In any sub-period, the past winner portfolios had higher relative downside betas and lower relative upside betas that the past loser portfolios. The asymmetry in the upside and downside betas was persistent in different periods of time.

2.6.CONCLUSION

Momentum strategies generate high returns with insignificant overall market risk. Therefore, the momentum return is either evidence for market inefficiency, or a compensation for another risk factor. In this paper, I provide a novel risk-based explanation for momentum returns. I show that once we separate the overall market risk into the upside and downside risks, the momentum strategies appear to have asymmetric risk profile: they are exposed to the downside risk, but hedge against the upside risk. Since the upside and downside risks are priced differently, the momentum return is a compensation for this risk asymmetry.

I consider US, global and regional momentum and reversal portfolios of individual stocks and global momentum portfolios of country indices and currencies. I show that the asymmetry in upside and downside market risks explains all cross-sections of momentum portfolio returns well. Past loser portfolios have lower downside risk and higher upside risk, whereas past winner portfolios have higher downside risk and lower upside risk and, hence, greater downside-upside risk asymmetry. For any set of momentum portfolios, the risk asymmetry is monotonically increasing with portfolio rank. The downside-risk CAPM explains the cross-section of momentum returns much better than the traditional CAPM. The estimates of the relative downside beta premium are always statistically significant and similar in magnitude to the estimates obtained for other asset markets. Therefore, the momentum return is not anomalous, but a compensation for the asymmetric upside and downside market risks.

Figure 2.1. Relative upside and downside risks of US momentum portfolios



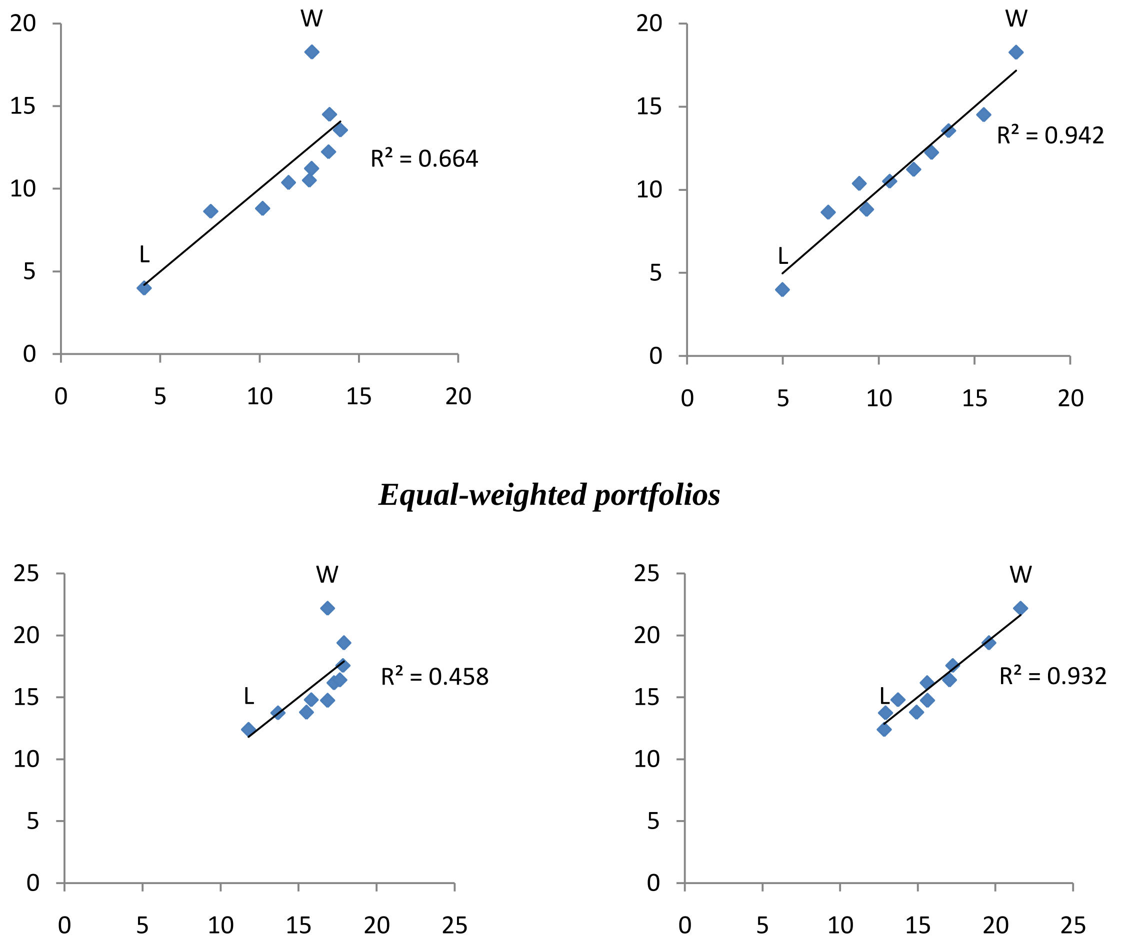
The figure shows the OLS estimates of relative downside and upside betas and beta asymmetry (β^{-}-β^{+}) of 10US value-weighted momentum portfolios, formed by sorting stocks at time t by their total return in time t-12 to t-2, and the winner-minus-loser (WML) portfolio. January 1927 - July 2013.

Figure 2.2. Predicted versus realized returns of US momentum portfolios

CAPM **Two-beta CAPM**

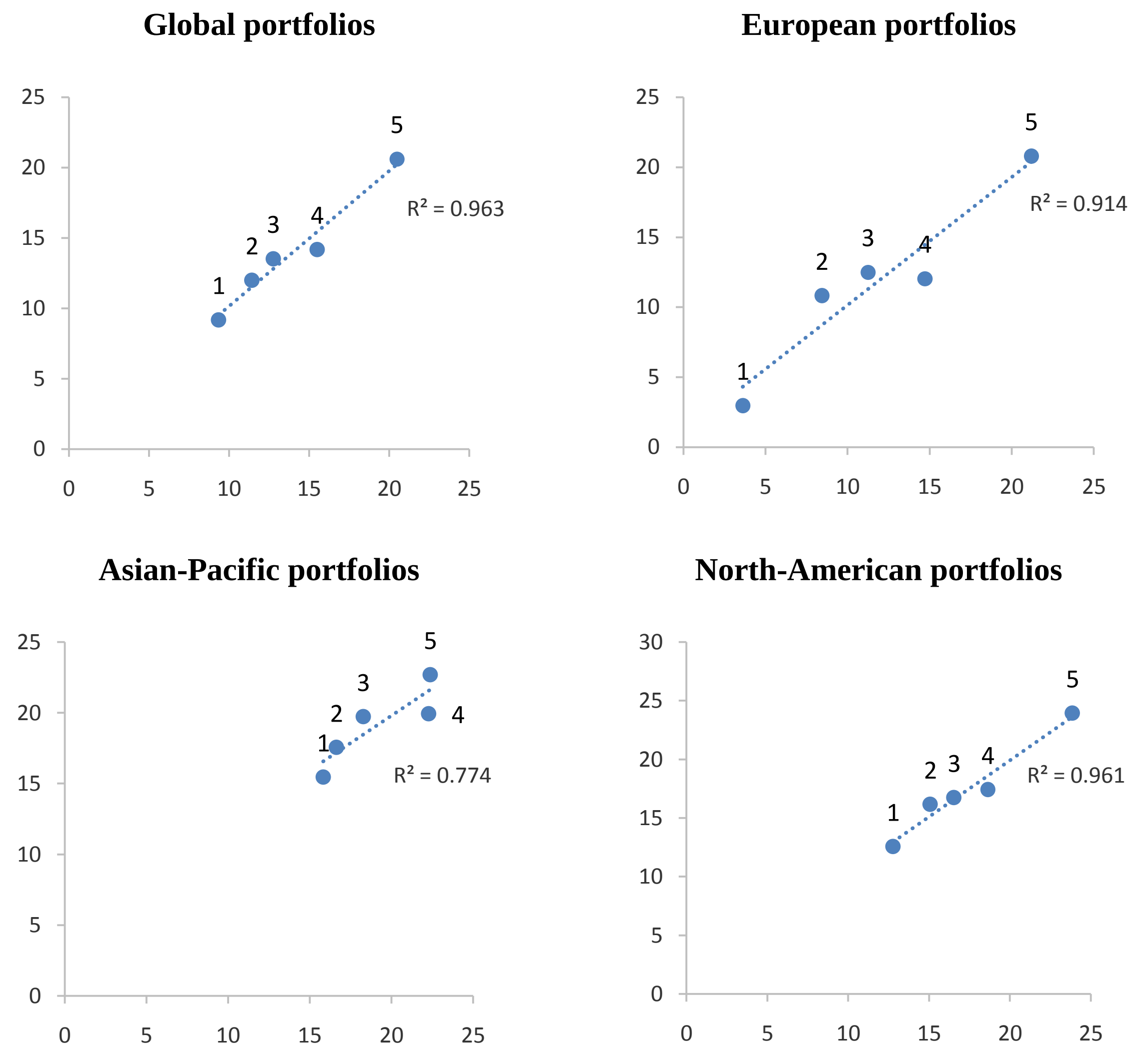
Value-weighted portfolios

Equal-weighted portfolios



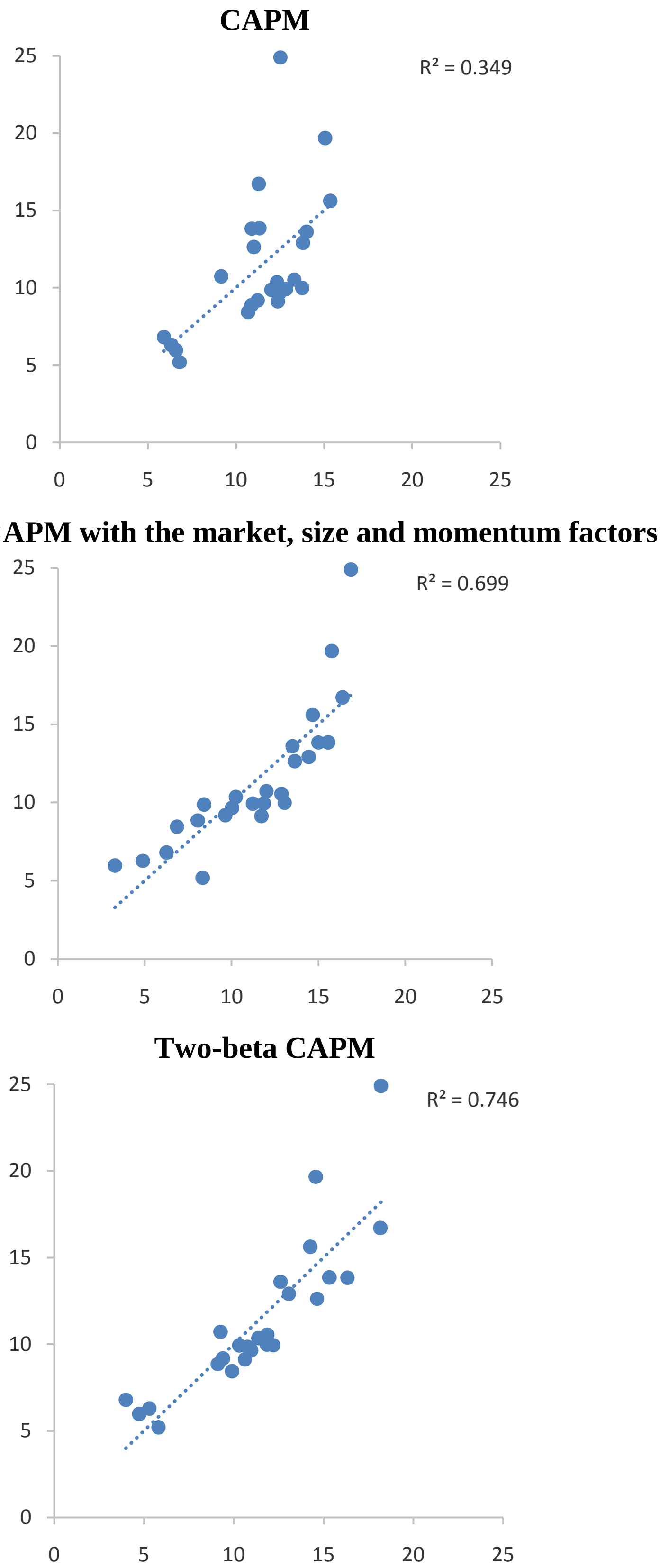
The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 10 US momentum portfolios, formed by sorting stocks at time t by their total return in time t-12 to t-2.The predictions are made assuming the CAPM (left-hand side) and the two-beta CAPM (right-hand side) using the OLS estimates.January 1927 - July 2013.

Figure 2.3. Predicted versus realized returns of global and regional momentum portfolios: Two-beta CAPM



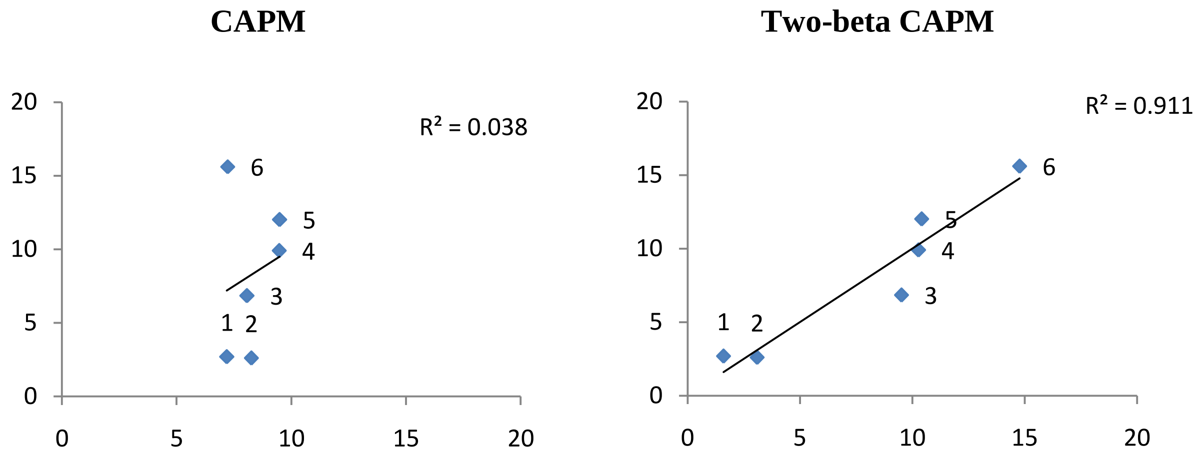
The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of global and regional momentum portfolios, formed by sorting stocks in the corresponding region at time t by their total return in time t-12 to t-2. The prediction is made assuming the two-beta CAPM using the OLS estimates. Nov 1990 - Aug 2013.

Figure 2.4. Predicted versus realized returns of 25 global size-momentum portfolios



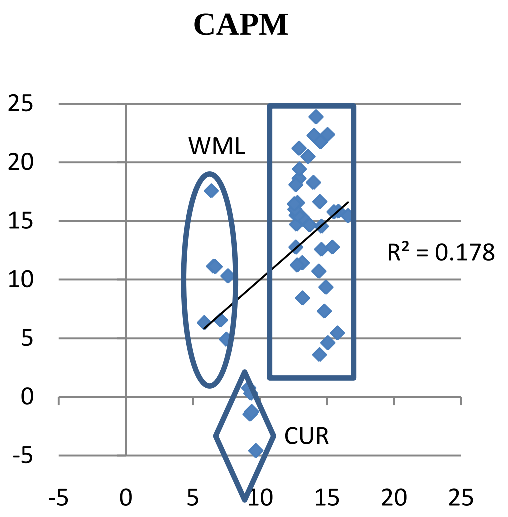
The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 25 global double-sorted size-momentum portfolios. The predictions are made using alternative factor models and OLS estimates. Nov 1990 - Aug 2013.

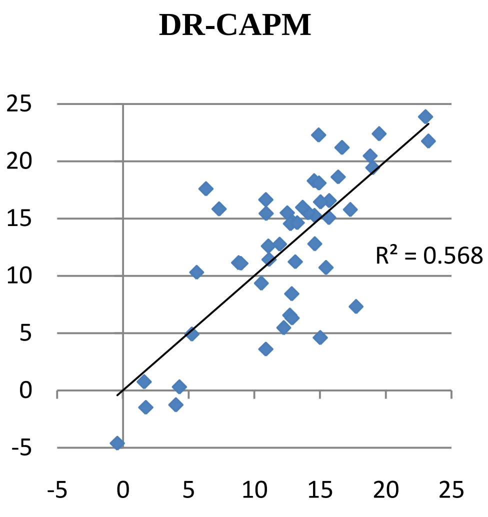
Figure 2.5. Predicted versus realized returns of momentum portfolios of country indices



The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 6 global momentum portfolios, formed by sorting 40 country indices at time t by their total return in time t-12 to t-2The predictions are made assuming the CAPM (left-hand side) and the two-beta CAPM (right-hand side) using the OLS estimates. Jan 1984 - Aug 2013.

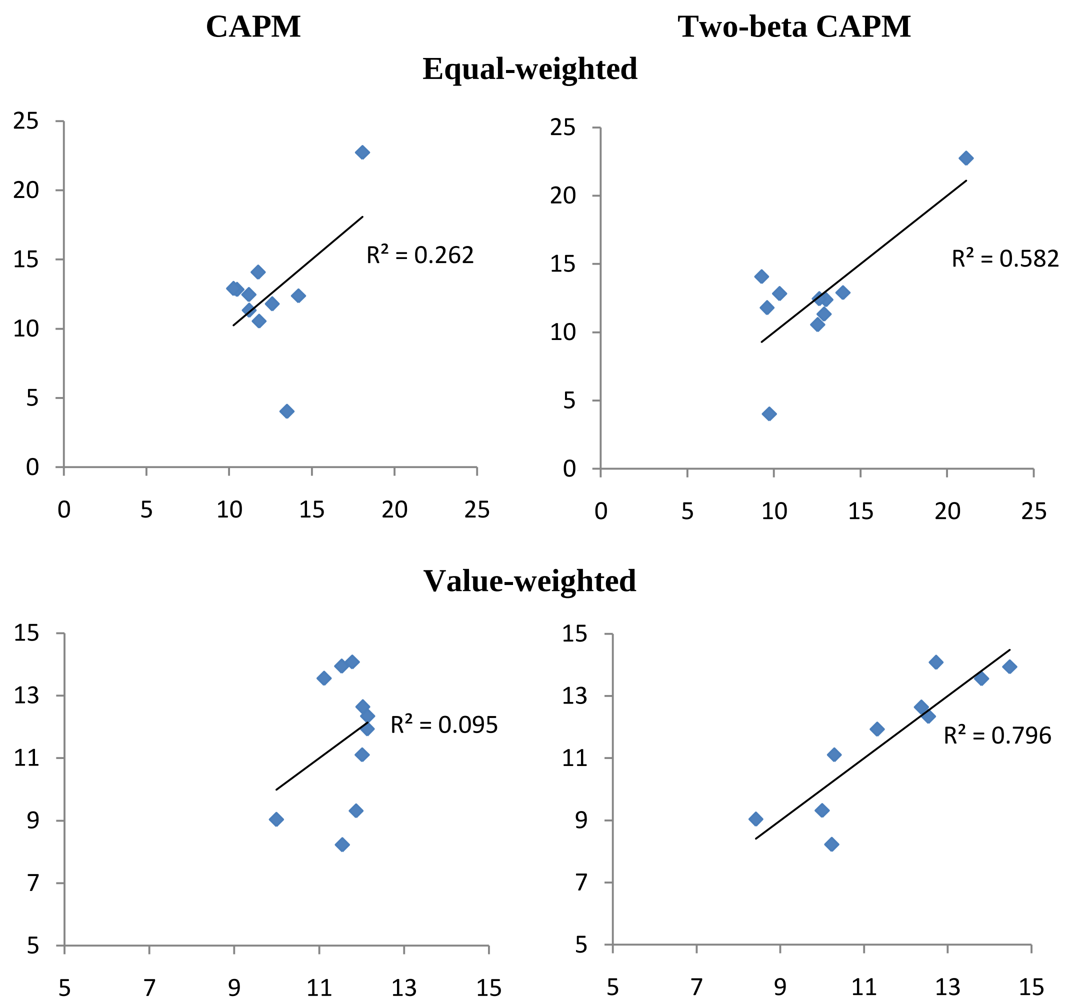
Figure 2.6. Predicted versus realized returns of 48 global and regional momentum portfolios





The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 48 global and regional momentum portfolios (10 US portfolios, 5 global, 5 European, 5 Asian-Pacific and 5 North-American portfolios of stocks, 6 portfolios of country indices and 5 currency portfolios, and 7 corresponding WML portfolios). All portfolios are formed by sorting base assets at time t by their total return in time t-12 to t-2. The predictions are made assuming the CAPM (left-hand side) and the DR-CAPM (right-hand side) using the OLS estimates. Nov 1990 - Aug 2013.

Figure 2.7. Predicted versus realized returns of US short-term reversal portfolios

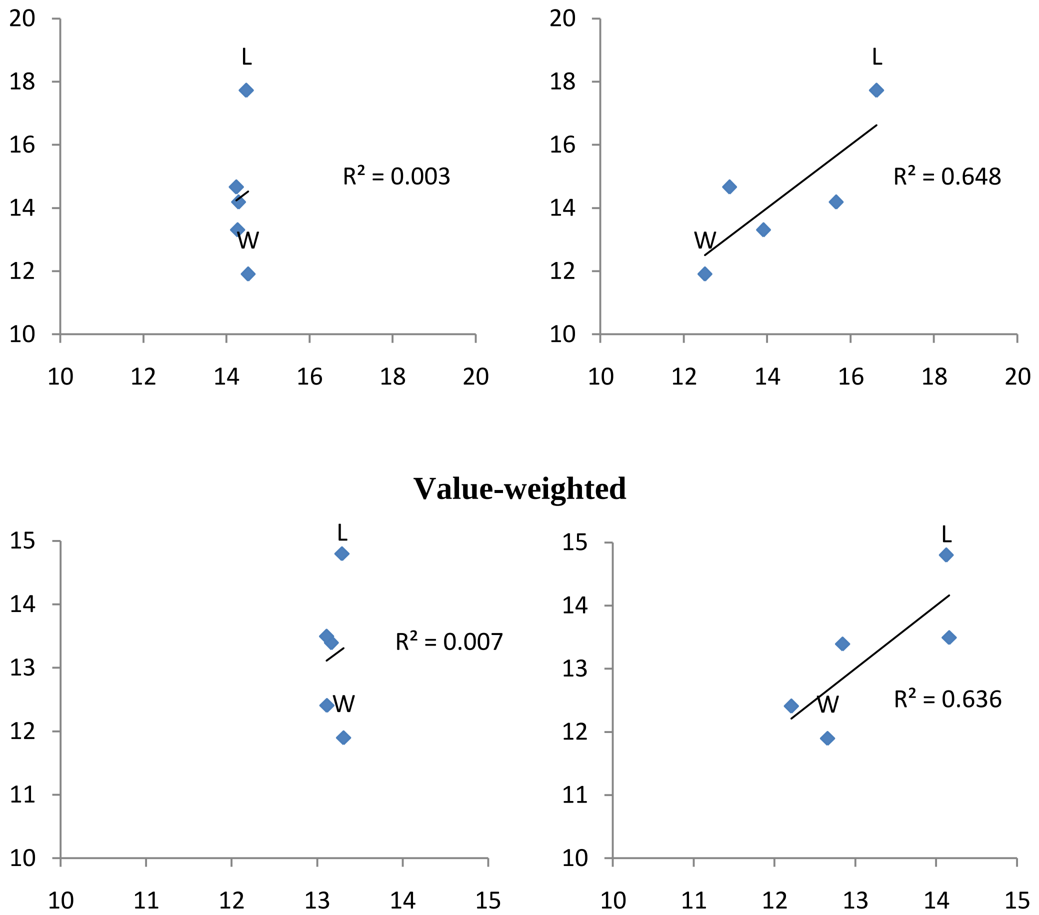


The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 10 US short-term reversal portfolios, formed by sorting individual stocks in month t by their return in month t-1. The predictions are made assuming the CAPM (left-hand side) and the two-beta CAPM (right-hand side) using the OLS estimates. Jan 1984 - Jul 2013.

Figure 2.8. Predicted versus realized returns of US long-term reversal portfolios

CAPM | **Two-beta CAPM**

Equal-weighted



The figures show predicted (on the horizontal axis) versus realized (on the vertical axis) returns of 5 US long-term reversal portfolios, formed by sorting individual stocks in month t by their return in the preceding 5-year period. The predictions are made assuming the CAPM (left-hand side) and the two-beta CAPM (right-hand side) using the OLS estimates. Jan 1984 - Jul 2013.

Table 2.1. Return and risk characteristics of US momentum portfolios

The table reports return and risk characteristics of 10 value-weighted and 10 equal-weighted US momentum portfolios, formed by sorting NYSE, AMEX, and NASDAQ stocks at time t by their total return in time t-12 to t-2, and the corresponding winner-minus-loser (WML) portfolios. The returns are annualized and expressed in percent. The reported betas are the OLS time-series estimates. The US market index serves as a proxy for the market portfolio. The momentum factor is the corresponding WML portfolio. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. Jan 1927 – July 2013.

	Low	2	3	4	5	6	7	8	9	High	WML
					Value-weighted						
Average return (%pa)	3.99	8.64	8.81	10.37	10.52	11.22	12.24	13.56	14.50	18.26	14.27
Standard deviation	117.98	98.05	84.72	77.30	71.82	69.90	66.74	64.74	68.33	78.62	95.44
Skewness	1.82	1.79	1.48	1.46	1.24	0.69	0.12	0.00	-0.32	-0.50	-2.44
Kurtosis	16.32	20.15	18.70	17.40	17.33	11.77	7.36	4.58	3.62	2.15	18.29
Market beta (β)	1.55	1.34	1.18	1.10	1.03	1.03	0.97	0.94	0.97	1.02	-0.52
	[18.34]	[16.16]	[17.58]	[23.61]	[21.37]	[35.25]	[45.72]	[45.46]	[29.33]	[15.14]	[-3.54]
Relative downside beta (β^{-}-β)	-0.28	-0.20	-0.13	-0.16	-0.10	-0.05	-0.02	0.02	0.09	0.17	0.44
Relative upside beta (β^{+}-β)	0.24	0.17	0.12	0.13	0.08	0.04	0.01	-0.01	-0.08	-0.14	-0.38
Betaasymmetry	-0.51	-0.37	-0.25	-0.29	-0.18	-0.09	-0.03	0.03	0.18	0.31	0.83
(β^{-}-β^{+})	[-2.67]	[-1.98]	[-1.76]	[-3.33]	[-1.45]	[-1.54]	[-0.55]	[0.71]	[2.23]	[2.37]	[2.64]
US momentum beta	-0.63	-0.39	-0.28	-0.19	-0.14	-0.05	0.02	0.10	0.17	0.37	1.00
	[-33.47]	[-17.06]	[-12.40]	[-12.04]	[-5.45]	[-2.72]	[1.46]	[7.02]	[10.88]	[19.67]	
					Equal-weighted						
Average return (%pa)	12.38	13.73	13.78	14.80	14.73	16.15	16.39	17.56	19.38	22.18	9.80
Standarddeviation	134.99	109.70	94.74	91.40	83.32	79.89	77.64	76.57	77.59	89.20	93.15
Skewness	2.85	3.12	2.08	2.53	1.74	1.44	1.07	0.94	0.10	0.11	-4.25
Kurtosis	22.15	31.71	20.01	24.76	20.35	16.11	14.51	13.55	5.80	5.71	38.34
Market beta (β)	1.59	1.43	1.28	1.25	1.16	1.13	1.09	1.08	1.07	1.16	-0.43
	[16.26]	[14.09]	[19.86]	[15.89]	[21.45]	[24.08]	[26.40]	[22.62]	[28.40]	[17.77]	[-3.08]
Relative downside beta (β^{-}-β)	-0.38	-0.32	-0.18	-0.23	-0.11	-0.10	-0.03	-0.01	0.09	0.15	0.53
Relative upside beta (β^{+}-β)	0.33	0.28	0.16	0.20	0.10	0.09	0.02	0.01	-0.08	-0.13	-0.46
Betaasymmetry	-0.71	-0.60	-0.34	-0.42	-0.21	-0.19	-0.05	-0.02	0.17	0.28	0.99
(β^{-}-β^{+})	[-2.69]	[-2.15]	[-2.10]	[-2.23]	[-1.50]	[-1.64]	[-0.47]	[-0.16]	[1.74]	[1.81]	[2.81]
US momentum beta	-0.83	-0.50	-0.34	-0.29	-0.21	-0.14	-0.07	0.00	0.06	0.17	1.00
	[-24.65]	[-12.00]	[-15.84]	[-9.36]	[-7.47]	[-6.64]	[-3.52]	[-0.15]	[2.53]	[4.91]	

Table 2.2. Cross-sectional regressions for US momentum portfolios

The table reports the Fama-MacBeth and efficient GMM estimates of risk premiums (in percent per month) obtained for 10 value-weighted and 10 equal-weighted US momentum portfolios. The US market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. J statistics for the over-identifying restrictions is also reported. P-value for J statistics is in parentheses. Jan 1927 – July 2013.

	Fama-MacBeth				**GMM**			
	CAPM		**DR-CAPM**		**CAPM**		**DR-CAPM**	
				Value-weighted				
Beta(β)	0.53	-1.35	0.75	-0.19	1.11	-0.81	0.71	0.12
	[2.96]	[-3.71]	[4.20]	[-0.51]	[7.11]	[-2.31]	[3.93]	[0.15]
Relative downside beta(β^{-}-β)			3.11	2.07			4.29	3.03
			[6.08]	[3.62]			[2.21]	[2.04]
Constant		2.15		0.99		1.57		0.65
		[6.37]		[2.95]		[4.76]		[0.79]
R^2adj	-0.66	0.62	0.80	0.93				
J-stat					20.49	22.57	4.57	4.39
					(0.02)	(0.00)	(0.80)	(0.73)
				Equal-weighted				
Beta(β)	0.83	-0.98	1.06	0.65	1.26	0.23	1.06	0.98
	[4.04]	[-2.28]	[5.18]	[1.34]	[7.28]	[0.62]	[4.78]	[1.36]
Relative downside beta(β^{-}-β)			2.25	1.90			2.27	2.19
			[5.59]	[4.10]			[2.84]	[2.25]
Constant		2.25		0.48		0.84		0.10
		[5.18]		[1.02]		[2.37]		[0.13]
R^2adj	-1.13	0.39	0.90	0.91				
J-stat					19.09	25.67	1.38	1.72
					(0.02)	(0.00)	(0.99)	(0.97)

Table2.3. Return and risk characteristics of global momentum portfolios

The table reports return and risk characteristics of 5 global equal-weighted momentum portfolios (panel A) and 5 regional equal-weighted momentum portfolios (panels B-D), and the corresponding winner-minus-loser (WML) momentum portfolios. All portfolios are formed by sorting individual stocks in the corresponding region at time t by their total return in time t-12 to t-2. All returns are converted to USD, annualized and expressed in percent. The reported betas are the OLS time-series estimates. The MSCI global market index serves as a proxy for the market portfolio. The global Fama-French momentum factor is used to estimate the momentum betas. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. Nov 1990 – Aug 2013.

	1	**2**	**3**	**4**	**5**	**WML**
Panel A: Global momentum portfolios						
Average return (% pa)	9.35	11.43	12.76	15.50	20.48	11.13
Standard deviation	75.04	51.93	46.72	48.23	62.46	47.84
Skewness	0.07	-0.64	-0.90	-0.85	-0.94	-1.73
Global market beta (β)	1.15	0.86	0.78	0.79	0.93	-0.22
	[11.50]	[14.06]	[17.05]	[18.34]	[15.58]	[-2.06]
Relative downside beta (β^{-}-β)	-0.04	0.03	0.07	0.08	0.18	0.22
Relative upside beta (β^{+}-β)	0.05	-0.04	-0.08	-0.09	-0.21	-0.26
Betaasymmetry(β^{-}-β^{+})	-0.10	0.07	0.15	0.17	0.39	0.49
	[-0.32]	[0.38]	[1.18]	[1.82]	[3.15]	[2.87]
Momentumbeta	-0.44	-0.16	0.00	0.18	0.46	0.90
	[-3.38]	[-2.88]	[0.12]	[3.65]	[4.99]	[17.99]
Av. number of stocks	5545	2558	2204	2145	2932	
Panel B: European momentum portfolios						
Average return (% pa)	3.60	8.42	11.23	14.71	21.18	17.58
Standard deviation	74.19	56.98	52.79	53.09	61.65	48.30
Skewness	0.07	-0.89	-0.98	-0.82	-0.61	-1.47
Global market beta (β)	1.07	0.87	0.80	0.79	0.82	-0.25
	[9.41]	[11.08]	[11.86]	[12.36]	[12.03]	[-2.27]
Relative downside beta (β^{-}-β)	-0.02	0.07	0.09	0.09	0.16	0.18
Relative upside beta (β^{+}-β)	0.02	-0.08	-0.10	-0.10	-0.19	-0.21
Betaasymmetry(β^{-}-β^{+})	-0.04	0.15	0.19	0.19	0.34	0.39
	[-0.13]	[0.60]	[0.99]	[1.18]	[2.07]	[2.26]
Momentumbeta	-0.43	-0.17	-0.04	0.11	0.30	0.73
	[-3.50]	[-2.80]	[-0.76]	[2.31]	[4.58]	[8.99]
Av. number of stocks	1968	884	750	705	966	

Table 2.3 (Continued). Return and risk characteristics of global momentum portfolios

The table reports return and risk characteristics of 5 global equal-weighted momentum portfolios (panel A) and 5 regional equal-weighted momentum portfolios (panels B-D), and the corresponding winner-minus-loser (WML) momentum portfolios. All portfolios are formed by sorting individual stocks in the corresponding region at time t by their total return in time t-12 to t-2. All returns are converted to USD, annualized and expressed in percent. The reported betas are the OLS time-series estimates. The MSCI global market index serves as a proxy for the market portfolio. The global Fama-French momentum factor is used to estimate the momentum betas. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. Nov 1990 – Aug 2013.

	1	**2**	**3**	**4**	**5**	**WML**
Panel C: Asian-Pacific momentum portfolios						
Average return (% pa)	15.83	16.63	18.28	22.27	22.38	6.55
Standard deviation	102.75	79.77	72.61	74.89	91.98	56.46
Skewness	0.30	-0.06	-0.63	-0.53	-1.03	-2.22
Global market beta (β)	1.30	1.08	1.00	1.00	1.17	-0.13
	[9.22]	[10.27]	[12.48]	[12.02]	[11.46]	[-2.66]
Relative downside beta (β^{-}-β)	-0.15	-0.02	0.07	0.08	0.14	0.29
Relative upside beta (β^{+}-β)	0.17	0.02	-0.09	-0.09	-0.17	-0.34
Betaasymmetry(β^{-}-β^{+})	-0.32	-0.05	0.16	0.17	0.31	0.62
	[-0.73]	[-0.14]	[0.70]	[0.80]	[1.38]	[3.06]
Momentumbeta	-0.19	-0.05	0.05	0.19	0.36	0.55
	[-1.04]	[-0.39]	[0.63]	[1.94]	[3.26]	[4.63]
Av. number of stocks	885	319	269	270	413	
Panel D: North-American momentum portfolios						
Average return (% pa)	12.77	15.07	16.54	18.63	23.86	11.09
Standard deviation	88.11	55.76	51.20	54.13	77.67	64.30
Skewness	0.31	-0.98	-1.04	-0.82	-0.28	-1.34
Global market beta (β)	1.23	0.88	0.80	0.82	1.03	-0.20
	[10.67]	[13.67]	[16.18]	[16.68]	[13.31]	[-3.07]
Relative downside beta (β^{-}-β)	0.02	0.12	0.14	0.15	0.25	0.22
Relative upside beta (β^{+}-β)	-0.03	-0.15	-0.17	-0.18	-0.29	-0.26
Betaasymmetry(β^{-}-β^{+})	0.05	0.27	0.31	0.33	0.54	0.49
	[0.16]	[1.49]	[2.37]	[2.94]	[2.88]	[2.08]
Momentumbeta	-0.51	-0.14	0.05	0.25	0.66	1.18
	[-2.90]	[-2.60]	[0.91]	[3.73]	[4.22]	[18.29]
Av. number of stocks	1990	861	733	753	1124	

Table 2.4. Cross-sectional regressions for global momentum portfolios

The table reports the Fama-MacBeth and efficient GMM estimates of risk premiums (in percent per month) obtained for global and regional equal-weighted momentum portfolios (five in each case). All portfolios are formed by sorting individual stocks in the corresponding region at time t by their total return in time t-12 to t-2. The MSCI global market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. J statistics for the over-identifying restrictions is also reported. P-value for J statistics is in parentheses. Nov 1990 – Aug 2013.

	Fama-MacBeth				**GMM**			
	CAPM		**DR-CAPM**		**CAPM**		**DR-CAPM**	
				Global				
Beta(β)	0.96	-0.80	0.66	0.43	1.83	-0.09	1.20	-0.21
	[2.44]	[-1.14]	[1.61]	[0.65]	[5.47]	[-0.17]	[2.54]	[-0.11]
Relative downside beta(β^{-}-β)			4.93	4.68			4.15	5.71
			[3.97]	[3.39]			[2.32]	[2.53]
Constant		1.63		0.22		0.84		0.95
		[3.61]		[0.50]		[2.44]		[0.80]
R^2adj	-0.45	-0.18	0.94	0.93				
J-stat					7.83	16.31	3.89	3.02
					(0.10)	(0.00)	(0.27)	(0.22)
				European				
Beta(β)	0.78	-3.49	0.12	0.90	2.10	-1.69	0.99	1.51
	[1.78]	[-3.65]	[0.25]	[0.68]	[4.91]	[-2.62]	[1.36]	[0.61]
Relative downside beta(β^{-}-β)			8.36	9.62			5.58	5.90
			[5.56]	[3.68]			[2.43]	[2.19]
Constant		3.77		-0.78		2.02		-0.47
		[5.24]		[-0.66]		[4.09]		[-0.22]
R^2adj	-0.28	0.38	0.87	0.83				
J-stat					8.11	95.78	1.42	1.40
					(0.09)	(0.00)	(0.70)	(0.50)
				Asian-Pacific				
Beta(β)	1.18	-0.76	1.14	0.53	2.32	-0.66	0.53	0.81
	[2.36]	[-0.86]	[2.24]	[0.67]	[5.09]	[-0.96]	[0.44]	[0.40]
Relative downside beta(β^{-}-β)			2.79	2.35			8.07	10.11
			[2.56]	[2.14]			[1.53]	[0.75]
Constant		2.17		0.69		1.98		-0.62
		[3.15]		[0.99]		[3.23]		[-0.18]
R^2adj	-0.79	-0.15	0.63	0.55				
J-stat					8.01	13.42	1.92	1.83
					(0.09)	(0.00)	(0.59)	(0.40)
				North-American				
Beta(β)	1.21	-0.42	0.56	0.49	2.04	13.25	0.61	0.40
	[3.13]	[-0.67]	[1.29]	[0.79]	[5.32]	[1.10]	[0.51]	[0.38]
Relative downside beta(β^{-}-β)			4.80	4.69			5.78	4.12
			[3.57]	[2.78]			[2.02]	[2.05]
Constant		1.60		0.09		-9.58		0.44
		[3.64]		[0.16]		[-0.96]		[0.69]
R^2adj	-0.66	-0.27	0.95	0.92				
J-stat					8.96	13.69	1.14	0.76
					(0.06)	(0.00)	(0.77)	(0.69)

Table 2.5. Returns and asymmetric betas of 25 global size-momentum portfolios

The table reports returns and betas of 25 global double-sorted size-momentum portfolios, the winner-minus-loser (WML) momentum portfolios and the small-minus-big (SMB) size portfolios. The returns are annualized and expressed in percent. The betas are the OLS time-series estimates. The global market index serves as a proxy for the market portfolio. T-statistics for the long-short portfolios are reported in brackets. Nov 1990 – Aug 2013.

	Average returns, % pa					
	1 - low	2	3	4	5 - high	**WML**
1 - small	10.72	13.61	15.62	19.67	24.91	**14.18**
2	5.20	9.12	9.98	12.91	16.70	**11.51**
3	6.80	9.18	9.92	10.54	13.83	**7.03**
4	6.28	8.87	9.65	9.95	13.85	**7.56**
5 - big	5.96	8.44	9.86	10.35	12.63	**6.67**
SMB	**4.76**	**5.17**	**5.75**	**9.32**	**12.27**	
	Beta asymmetry (β^{-}-β^{+})					
	1 - low	2	3	4	5 - high	**WML**
1 - small	-0.03	0.14	0.23	0.24	0.43	**0.46 [3.17]**
2	-0.21	0.04	0.10	0.17	0.43	**0.64 [3.53]**
3	-0.30	-0.02	0.02	0.10	0.33	**0.64 [3.29]**
4	-0.24	-0.04	0.06	0.12	0.28	**0.52 [2.52]**
5 - big	-0.26	0.00	0.05	0.08	0.25	**0.51 [2.39]**
SMB	**0.23 [1.32]**	**0.14 [1.07]**	**0.18 [1.60]**	**0.16 [1.34]**	**0.18 [1.02]**	
	Relative downside beta(β^{-}-β)					
	1 - low	2	3	4	5 - high	**WML**
1 - small	-0.01	0.07	0.10	0.11	0.20	**0.21**
2	-0.10	0.02	0.05	0.08	0.20	**0.29**
3	-0.14	-0.01	0.01	0.05	0.15	**0.29**
4	-0.11	-0.02	0.03	0.06	0.13	**0.24**
5 - big	-0.12	0.00	0.02	0.04	0.11	**0.23**
SMB	**0.11**	**0.06**	**0.08**	**0.08**	**0.08**	
	Relative upside beta (β^{+}-β)					
	1 - low	2	3	4	5 - high	**WML**
1 - small	0.02	-0.08	-0.12	-0.13	-0.23	**-0.25**
2	0.11	-0.02	-0.06	-0.09	-0.23	**-0.35**
3	0.16	0.01	-0.01	-0.06	-0.18	**-0.34**
4	0.13	0.02	-0.03	-0.07	-0.15	**-0.28**
5 - big	0.14	0.00	-0.03	-0.04	-0.13	**-0.28**
SMB	**-0.13**	**-0.08**	**-0.10**	**-0.09**	**-0.10**	

Table 2.6. Cross-sectional regressions for 25 size-momentum portfolios

The table reports the Fama-MacBeth and the efficient GMM estimates of risk premiums (in percent per month) obtained for 25 global double-sorted size-momentum portfolios. Alternative multi-factor models are estimated in columns (1)-(4). The global market factor, the global momentum factor and the global size factor are used as risk factors. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. J statistics for the over-identifying restrictions is also reported. P-value for J statistics is in parentheses. Nov 1990 – Aug 2013.

	Fama-MacBeth				GMM			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Beta(β)	-1,30	0,07	-0,75	0,06	-3,99	0,81	-0,96	0,45
	[-2,69]	[0,14]	[-2,00]	[0,14]	[-7,64]	[0,69]	[-2,80]	[0,32]
Relative downside beta(β^{-}-β)		3,61		5,57		5,67		5,27
		[2,64]		[5,12]		[2,03]		[5,19]
SMB beta			0,48	0,55			1,23	0,79
			[2,84]	[3,15]			[7,93]	[4,51]
Momentumbeta			0,62	0,62			0,42	0,41
			[2,13]	[2,15]			[1,79]	[1,86]
Constant	1,95	0,50	1,12	0,34	4,71	-0,23	0,94	-0,32
	[4,90]	[1,23]	[3,51]	[0,90]	[8,90]	[-0,22]	[3,17]	[-0,35]
R2 adj	0,32	0,72	0,66	0,79				
J-stat					22,24	29,04	22,10	23,77
					(0,51)	(0,14)	(0,39)	(0,25)

Table 2.7. Return and risk characteristics of momentum portfolios of country indices

The table reports return and risk characteristics of 6 global momentum portfolios, formed by sorting 40 country indices at time t by their total return in time t-12 to t-2, the winner-minus-loser (WML) portfolio and the US market index. All returns are annualized and expressed in percent. The reported betas are the OLS time-series estimates. The MSCI global market index serves as a proxy for the market portfolio. The global Fama-French momentum factor is used to estimate the momentum betas. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. Jan 1984 – Aug 2013.

	1	**2**	**3**	**4**	**5**	**6**	**WML**	**US ret**
Returnin local currency	8,05	6,20	10,16	11,47	14,01	34,23	26,18	8,99
Exchangeratereturn	-1,37	0,38	0,67	2,42	1,99	-14,64	-13,26	
Returnin USD	6,68	6,59	10,83	13,89	16,00	19,59	12,92	8,99
Return in excess of US return	-2,31	-2,40	1,84	4,90	7,01	10,60		
	[-0,58]	[-0,83]	[0,58]	[1,71]	[2,24]	[2,71]		
Standard deviation	80,69	70,23	69,72	66,83	68,26	85,43	69,32	53,38
Skewness	-0,31	-0,53	-0,67	-0,71	-0,71	-0,68	-0,05	-0,74
Global market beta (β)	1,12	1,08	1,08	1,02	1,02	1,12	0,00	0,87
	[14,68]	[16,47]	[22,40]	[20,29]	[18,63]	[13,19]	[-0,01]	[23,60]
Relative downside beta (β^{-}-β)	0,07	0,06	0,18	0,17	0,16	0,34	0,27	0,08
Relative upside beta (β^{+}-β)	-0,08	-0,06	-0,20	-0,18	-0,17	-0,37	-0,29	-0,08
Betaasymmetry (β^{-}-β^{+})	0,15	0,12	0,38	0,34	0,34	0,71	0,57	0,15
	[0,76]	[0,65]	[3,02]	[2,68]	[2,09]	[3,13]	[2,12]	[1,81]
Globalmomentumbeta	-0,32	-0,15	0,04	0,05	0,08	0,13	0,45	-0,02
	[-4,22]	[-1,95]	[0,48]	[0,72]	[1,26]	[2,05]	[5,20]	[-0,56]

Table 2.8. Cross-sectional regressions for momentum portfolios of country indices

The table reports the Fama-MacBeth and GMM estimates of risk premiums (in percent per month) obtained for the 6 global momentum portfolios, formed by sorting 40 country indices at time t by their total return in time t-12 to t-2. The MSCI global market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. J statistics for the over-identifying restrictions is also reported. P-value for J statistics is in parentheses. Jan 1984 – Aug 2013.

	Fama-MacBeth				**GMM**			
	CAPM		**DR-CAPM**		**CAPM**		**DR-CAPM**	
Beta(β)	0.95	-1.69	0.35	-3.31	0.84	-45.28	0.00	-2.56
	[2.96]	[-0.95]	[1.06]	[-1.75]	[2.37]	[-0.31]	[-0.01]	[-0.87]
Relative downside beta(β^{-}-β)			3.89	4.08			4.73	4.37
			[3.92]	[4.02]			[2.11]	[2.10]
Constant		2.84		3.90		49.33		2.80
		[1.55]		[2.06]		[0.31]		[0.94]
R^2adj	-0.05	-0.21	0.72	0.90				
J-stat					13.42	5.59	9.23	6.09
					(0.02)	(0.23)	(0.06)	(0.11)

Table 2.9. Returns, risks and risk premiums of currency momentum portfolios

The table reports return and risk characteristics of 5currency momentum portfolios, formed by sorting currencies at time t by their returns in time t-12 to t-2 and held for 1 month, and the 5-1 winner-minus-loser (WML) portfolio (panel A) and the Fama-MacBeth and efficient GMM estimates of risk premiums (panel B). The returns are annualized, whereas the risk premiums are expressed in percent per month. The reported betas are the OLS time-series estimates. The MSCI global market index serves as a proxy for the market portfolio. The global Fama-French momentum factor is used to estimate the equity momentum betas. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. J statistics for the over-identifying restrictions is also reported. P-value for J statistics is in parentheses. Nov 1984 – Aug 2013.

	Panel A: Time-series regressions					
	1	**2**	**3**	**4**	**5**	**WML**
Exchange rate return (% pa)	-5.47	-0.36	0.95	2.65	2,35	7,82
Standard deviation	34.27	27.51	30.66	29.78	29.07	36.55
Skewness	-0.70	0.30	-0.28	-0.31	-0.65	0.75
Global market beta (β)	0.24	0.18	0.22	0.20	0.21	-0.03
	[5.38]	[4.32]	[4.65]	[4.60]	[5.12]	[-0.68]
Relative downside beta (β^{-}-β)	-0.14	-0.07	-0.05	-0.09	-0.01	0.13
Relative upside beta (β^{+}-β)	0.17	0.08	0.06	0.11	0.01	-0.16
Betaasymmetry (β^{-}-β^{+})	-0.31	-0.15	-0.12	-0.19	-0.01	0.30
	[-2.22]	[-1.42]	[-1.03]	[-1.78]	[-0.12]	[2.43]
Global equity momentum beta	-0.10	-0.06	0.02	0.03	0.09	0.19
	[-2.51]	[-1.55]	[0.61]	[0.83]	[2.94]	[4.59]

	Panel B: Cross-sectional regressions			
	Fama-MacBeth		**GMM**	
	CAPM	**DR-CAPM**	**CAPM**	**DR-CAPM**
Beta(β)	-1.56	-0.21	-1.91	1.10
	[-2.59]	[-0.27]	[-3.24]	[0.55]
Relative downside beta (β^{-}-β)		3.97		4.74
		[2.80]		[2.42]
R^2adj	0.15	0.47		
J-stat			7.91	7.99
			(0.09)	(0.09)

Table 2.10. Correlation matrix for winner-minus-loser momentum portfolios

The table reports correlation coefficients of returns of 7 global and regional WML portfolios and the global Fama-French momentum factor. T-statistics are in brackets. Nov 1990 – Aug 2013.

	US	Global	European	Asian-Pacific	North-American	Country indices	Curren cies	FF mom factor
US	1.00							
Global	0.80	1.00						
	[21.68]							
European	0.56	0.81	1.00					
	[11.06]	[22.86]						
Asian-Pacific	0.39	0.56	0.29	1.00				
	[7.06]	[11.05]	[5.01]					
North-American	0.89	0.89	0.64	0.44	1.00			
	[32.34]	[32.63]	[13.60]	[7.97]				
Country indices	0.24	0.33	0.21	0.34	0.27	1.00		
	[4.01]	[5.76]	[3.53]	[5.93]	[4.69]			
Currencies	0.15	0.21	0.20	0.33	0.17	0.20	1.00	
	[2.49]	[3.55]	[3.35]	[5.67]	[2.92]	[3.42]		
Global FF mom factor	0.72	0.92	0.76	0.48	0.88	0.37	0.26	1.00
	[17.13]	[38.91]	[19.22]	[8.98]	[30.17]	[6.50]	[4.53]	

Table 2.11. Cross-sectional regressions for 48 global and regional momentum portfolios

The table reports the Fama-MacBeth estimates of risk premiums (in percent per month) obtained for 48 global and regional momentum portfolios. Alternative multi-factor models are estimated in columns (1)-(5). The global market factor and the global momentum factor are used as risk factors. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. Nov 1990 – Aug 2013.

	(1)	(2)	(3)	(4)	(5)
Beta(β)	1.14	0.51	1.10	0.88	1.02
	[3.03]	[1.14]	[2.67]	[2.12]	[2.40]
Relative downside beta (β^{-}-β)				3.94	2.79
				[3.99]	[2.06]
Momentum beta			1.04		0.44
			[3.39]		[1.02]
Constant		0.66	0.11	0.04	-0.01
		[3.75]	[1.08]	[0.43]	[-0.06]
R^2 adj	-0.21	0.16	0.49	0.55	0.57

Table 2.12. Cross-sectional regressions for reversal portfolios

The table reports the Fama-MacBeth estimates of risk premiums (in percent per month) obtained for 10 value-weighted US short-term reversal portfolios and 10 value-weighted US long-term reversal portfolios. The short-term reversal portfolios are formed by sorting stocks in month t by their return in month t-1. The long-term reversal portfolios are formed by sorting stocks in month t by their return in the preceding 5-year period. The US market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using NW heteroskedasticity consistent standard errors. The sample period is Jan 1927 – July 2013 for the short-term reversal portfolios and Jan 1931 – July 2013 for the long-term reversal portfolios.

	CAPM		**DR-CAPM**	
	Short-term reversal			
Beta(β)	0.65	0.88	0.71	1.02
	[3.70]	[2.37]	[4.04]	[2.59]
Relative downside beta(β^{-}-β)			1.62	1.67
			[2.35]	[2.35]
Constant		-0.26		-0.34
		[-0.69]		[-0.87]
R^2	0.18	0.19	0.35	0.38
	Long-term reversal			
Beta(β)	0.74	1.28	0.64	0.49
	[2.05]	[2.52]	[1.48]	[1.10]
Relative downside beta(β^{-}-β)			0.93	1.04
			[1.62]	[1.73]
Constant		-0.61		0.15
		[-1.23]		[0.36]
R^2	0.61	0.74	0.93	0.94

Table 2.13. Return and risk characteristics of US momentum portfolios in sub-periods

The table reports return and risk characteristics of 10 value-weighted US momentum portfolios, formed by sorting NYSE, AMEX, and NASDAQ stocks at time t by their total return in time t-12 to t-2, and the corresponding winner-minus-loser (WML) portfolios in sub-periods. The returns are annualized and expressed in percent. The reported betas are the OLS time-series estimates. The US market index serves as a proxy for the market portfolio. Jan 1927 – July 2013.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**WML**
						1927-1969					
Average return (%pa)	6,00	8,63	6,74	9,27	10,81	11,21	12,59	13,77	15,42	19,27	13,27
US market beta	1,60	1,43	1,26	1,18	1,10	1,08	1,02	0,95	0,97	0,95	-0,66
Relativedownsidebeta	-0,34	-0,23	-0,13	-0,20	-0,12	-0,07	-0,02	0,03	0,11	0,21	0,55
Relativeupsidebeta	0,28	0,19	0,10	0,16	0,10	0,06	0,01	-0,03	-0,09	-0,18	-0,45
Betaasymmetry	-0,62	-0,41	-0,23	-0,36	-0,22	-0,14	-0,03	0,06	0,20	0,39	1,00
						1970-2013					
Average return (%pa)	2,01	8,66	10,85	11,47	10,23	11,22	11,90	13,34	13,60	17,26	15,25
US market beta	1,45	1,19	1,03	0,96	0,92	0,93	0,89	0,91	0,97	1,16	-0,29
Relativedownsidebeta	-0,13	-0,12	-0,14	-0,06	-0,03	0,02	0,00	-0,01	0,07	0,06	0,19
Relativeupsidebeta	0,12	0,12	0,13	0,06	0,03	-0,02	0,00	0,01	-0,06	-0,05	-0,18
Betaasymmetry	-0,25	-0,24	-0,27	-0,12	-0,06	0,04	0,00	-0,02	0,13	0,11	0,37
						2000-2013					
Average return (%pa)	2,86	6,38	6,83	9,23	8,52	6,42	7,67	7,52	6,27	7,19	4,34
US market beta	1,95	1,41	1,14	0,98	0,88	0,84	0,78	0,78	0,86	1,08	-0,86
Relativedownsidebeta	-0,45	-0,16	-0,20	-0,10	-0,15	0,05	-0,03	0,04	0,08	0,07	0,53
Relativeupsidebeta	0,55	0,20	0,25	0,12	0,18	-0,06	0,04	-0,05	-0,10	-0,09	-0,64
Betaasymmetry	-1,00	-0,36	-0,45	-0,21	-0,33	0,11	-0,07	0,09	0,18	0,17	1,17

Chapter 3

Downside Market Risk of Carry Trades

3.1. INTRODUCTION

One of the puzzles in international finance that challenges traditional theory is the forward premium puzzle, or the violation of uncovered interest parity (UIP). According to UIP, free capital mobility ensures that investments in different currencies with different levels of local interest rates do not consistently generate excess returns because a negative interest rate differential should be compensated by the expected exchange rate appreciation of the target currency or the forward premium. In reality, however, investments in high-interest currencies consistently generate higher excess returns than investments in low-interest currencies. This empirical 'anomaly' has led to the growing popularity of carry trades – an investment strategy in which an investor borrows in low-interest currencies and invests in high-interest currencies.

The aim of this paper is to answer the following question: are the high returns to carry trades a *fair* compensation for their risk? Brunnermeier at al. (2008) show that high-interest currencies tend to crash occasionally and that their returns are negatively skewed[10]. However, non-systematic crashes should not be relevant to a diversifying investor and thus cannot rationalize high returns. What is relevant is the systematic covariance of carry trade returns with the stochastic discount factor.

There is an ongoing debate as to whether carry trade portfolios have significant covariances (or betas) with the stochastic discount factor and whether these covariances can explain the cross-section of currency returns. Lustig and Verdelhan (2007) suggest that the consumption CAPM can explain the returns to carry trades because higher interest rate currencies have higher consumption betas. However, Burnside (2011) argues that the consumption betas of currency portfolios are statistically insignificant and economically too

[10] A number of papers quantify the crash risk of carry trades and estimate the crash risk premium (e.g., Farhi et al., 2013; Jurek, 2014; Chernov et al., 2013).

small to rationalize high carry trade returns, and he concludes that consumption risk cannot explain any of the cross-sectional variation in the expected returns of currency portfolios. Burnside (2012) investigates whether traditional factor models, the CAPM, the Fama-French three-factor model and the CAPM with industrial production, can explain the returns to carry trades. He finds that these models do not have sufficient explanatory power, either because the returns to carry trade portfolios are uncorrelated with US market factors or because the market betas are too small and the models estimated for currency and stock portfolios jointly are rejected. The author concludes that 'there is no unifying risk-based explanation of returns in these two markets'.

In this chapter, I propose the global downside market risk factor to explain currency returns. When we examine the downside market risk of carry trade portfolios, we observe a clear risk-return relationship. High interest rate currencies have high and statistically significant downside market risk, which is measured by the downside beta, the 'disaster beta' or the coskewness[11] with respect to the global stock market return; by contrast, low interest rate currencies have zero downside risk and hence can serve as a hedging instrument. Whereas the consumption betas or traditional market betas of carry trade long-short portfolios are rather small, the downside market betas are several times higher and statistically significant, especially if we measure them in the worst states of the world (e.g., when there is a market crash or a disaster event).

I show that the spread in the downside market betas and the coskewness across currency portfolios sorted by interest rate is sufficient to justify the spread in their returns. The GMM estimates of the downside beta and coskewness premiums in the currency market are highly significant. Moreover, the estimation of the downside beta or coskewness CAPM for currency and stock portfolios *jointly* produces a good fit of the model, whereas the traditional CAPM is

11 The downside beta is defined as the market beta conditional on the negative market return(the downside market factor beta); the 'disaster beta' is defined as the market beta in times of economic, political or natural disasters (the appendix provides a list of disasters); and coskewness is defined as the beta of the squared market return (the market volatility factor beta).

rejected on several grounds[12]. The downside risk has much higher explanatory power for the cross-section of returns in both markets, and the downside risk premiums are similar in both markets and are close to the theoretical values. In fact, I cannot reject the hypothesis that the downside risk is priced similarly in the currency and stock markets. I conclude that the high excess returns to carry trades are not a free lunch but rather *fair* compensation for their high *downside* market risk.

The estimates for the downside beta premium are approximately 1-2 percent per month, and the estimates for the coskewness premium are approximately minus 0.4-0.6 percent per month, depending on the specification[13]. An easy calculation allows us to obtain the expected excess return on a currency or stock portfolio with a particular level of downside risk. For example, the high-interest currency portfolio of developed countries had a downside beta of 0.38 and coskewness of -1.37 in 2000-2013. Multiplied by the corresponding monthly risk premiums and annualized, the expected return on this portfolio is calculated to be 6-8 percent per annum, which is similar to the historical return for this portfolio during this period. The high-interest currency portfolio of emerging markets had downside risk and return that were almost twice as high.

The results are robust to different levels of diversification within carry trade portfolios, different estimation methods employed (GMM with identity and efficient weighting matrices and Fama-MacBeth with time-varying betas), different cut-off levels for the downside betas, different samples of countries (the entire sample of developed and emerging economies as well as a sub-sample of developed countries) and different time periods. My downside market risk factor also wins the 'horse race' between alternative risk factors previously proposed in the literature on carry trades. The results are even stronger in the first decade of the 21st century – a period of rising popularity for carry trades among institutional investors (Jylhä

12 The spread in the traditional market betas across currency portfolios is insufficient, the estimate of the market beta premium is too high relative to its theoretical value, and the overall fit of the model is worse in both the currency and stock markets.

13 These estimates are obtained for stock and currency portfolios sorted by downside betas, as well as for carry trade portfolios of developed countries.

and Suominen, 2011)[14]. Lettau et al. (2014) provide further evidence in favor of the downside risk CAPM for the cross-section of currency, equity, bond and commodity portfolios.

In theory, the downside risk is a better measure of risk because it shows the covariance of an asset's return with the market in the worst states of the world when the overall market performs poorly and when the marginal utility of investors is high. If an asset also performs poorly in such states, then it is highly unattractive and should provide high expected returns. Ang, Chen and Xing (2006)provide an asset pricing model with downside and upside betas and empirically show that the downside beta has greater explanatory power in the stock market than the traditional beta. In an alternative asset pricing model – the three-moment CAPM by Harvey and Siddique (2000) – assets with lower coskewness with the market should provide higher expected returns because they perform poorly in states of high market volatility. The authors show that adding coskewness to the asset pricing regressions improves their explanatory power in the cross-section of stock returns. Coskewness can be considered a complimentary measure of downside risk because high market volatility is typically observed on the downside.

Empirically, the co-movement of several major currencies with the stock market has already been explored by Campbell et al. (2010) and Ranaldo and Söderlind (2010). Campbell et al. (2010) find a positive correlation of the Australian dollar and the Canadian dollar with the global equity markets and a negative correlation of the euro and the Swiss franc (the Japanese yen, the British pound and the US dollar fall in the middle of the two extremes). A high-frequency analysis in Ranaldo and Söderlind (2010) uncovers a similar pattern: the Swiss franc and the Japanese yen (and, to a lesser extent, the euro) appreciate when the US stock market declines, whereas the opposite is observed for the British pound. The 'safe haven' properties of the Swiss franc and the Japanese yen are confirmed in periods of political, natural or financial disaster. Although these two studies do not examine carry trades

[14] Jylhä and Suominen (2011) show that the tremendous growth in hedge funds' assets under management led to their greater influence in currency and bond markets and carry trade returns.

explicitly, their findings suggest that there is a particular relationship between local interest rates and the hedging properties of the currencies. In both papers, the currencies that move in the opposite direction to the stock market are also the most common funding currencies for carry trades (the Japanese yen and the Swiss franc), whereas the currencies with the highest exposure to the stock market are the usual target currencies. Hence, carry trades may be prone to high stock market risk, and this idea is explored thoroughly in my paper.

Rather than examining single currencies, I form portfolios of currencies sorted by the forward discount in the same manner as a carry trade is performed. This portfolio approach allows me to diversify the idiosyncratic risk and to concentrate on those properties that are attributable to currencies with different levels of interest rates. I include 42 developed and emerging economies in the sample, hence providing evidence for a much wider spectrum of currencies than in the papers cited above. I show that there is a systematic positive relationship between the global market risk of a currency and the local interest rate level, and this relationship is stronger for emerging market currencies. Moreover, this relationship is even stronger if we measure the market risk on the downside. High-interest currencies tend to crash along with the stock market, whereas low-interest currencies represent a 'safe haven'.

The remainder of the paper is organized as follows. In section 3.2, I briefly review the related empirical literature on currency returns and describe the theoretical asset pricing models with downside risk to motivate my risk measures. Section 3.3 is devoted to the data description and the currency portfolio formation. In section 3.4, I present the portfolio statistics and the main results of the estimation of alternative asset-pricing models by GMM. I compare the downside risk pricing in the currency and stock markets, vary thresholds for the downside beta and propose the 'disaster beta' as an alternative measure of downside risk. Section 3.5 is devoted to robustness tests. I study a sub-sample of developed countries and the more recent period of active carry trades, run 'horse races' between alternative risk factors, previously proposed in the literature, sort currencies by their downside betas and nominal interest rates rather than forward discounts, and perform Fama-MacBeth (1973) estimations with time-varying betas. Section 3.6 concludes the paper.

3.2. RELATED LITERATURE

3.2.1.EMPIRICAL LITERATURE ON CURRENCY RETURNS

Lustig and Verdelhan (2007) were among the first researchers to sort currencies by nominal interest rate level into portfolios and to study the cross-section of returns to these carry trade portfolios. They examine carry trades through the consumption CAPM lens and find that returns of high-interest currencies co-move with US non-durable and durable consumption growth, whereas returns of low-interest currencies serve as a hedge against domestic consumption risk. The authors conclude that the high average returns to carry trades compensate for the consumption risk because carry trades yield low returns when consumption growth is low and when the marginal utility of wealth is high. The relevance of the consumption CAPM framework for explaining currency returns was also confirmed by De Santis and Fornari (2008) for several European countries.

However, Burnside (2011) argues that the consumption risk explains none of the cross-sectional variation in carry trade returns. He finds that although the consumption betas of carry trade portfolios increase with the interest rate level, none are statistically different from zero, and there is no statistically significant spread in these betas. If the rank of betas is low, perhaps zero, then there are problems with weak identification of the beta premium. Moreover, the estimates of the consumption risk premium in the second-pass regressions in Lustig and Verdelhan (2007) do not account for the fact that the betas are generated regressors. Burnside (2011) shows that the estimates of the consumption risk premium are statistically insignificant once the standard errors are appropriately corrected (Shanken, 1992, or GMM). Furthermore, the consumption CAPM performs poorly (low R^2) if the constant is restricted to zero. Therefore, the validity of the consumption CAPM for currency returns is rejected on many grounds.

Subsequently, Lustig and Verdelhan (2011) provide additional evidence in favor of the consumption CAPM; their results are particularly visible during the global financial crisis of 2008, when carry trades crashed and consumption growth was low. By examining data with higher frequency, the authors show that the consumption risk factor loadings of carry returns vary over time and tend to increase during recessions and other crisis episodes. Therefore, their estimates of consumption betas on quarterly data understate the true risk. These researchers also provide evidence of the US stock market risk of carry trades and show that the correlation with the stock market increases during episodes of financial crisis. Overall, Lustig and Verdelhan (2011) conclude that 'the forward premium puzzle has a risk-based explanation'.

Burnside (2012) provides further evidence against the market risk-based explanation of carry trade returns. He tests whether the CAPM, the Fama-French three-factor model, and models with industrial production and stock market volatility can explain the returns to two currency portfolios: an equally weighted portfolio of all currencies and an HML portfolio with a long position in high-interest currencies and a short position in low-interest currencies. The author finds that the US market betas of these two portfolios are too small to rationalize their returns. He estimates the asset-pricing models using the 25 Fama-French stock portfolios and the two currency portfolios together and finds that the pricing errors for the currency portfolios are significant and that the models are rejected. Burnside (2012) concludes that the traditional risk factors that explain stock returns cannot explain the returns to carry trades. A discussion of his estimation methods is given in section 3.4.2 of this paper.

Meanwhile, other risk factors are proposed to explain currency returns. These risk factors are derived from the currency portfolios themselves, sorted by certain characteristics. Examples are the HML carry factor (Lustig et al., 2011), global currency volatility factor

(Menkhoff et al., 2012a), global currency skewness factor (Rafferty, 2012), FX correlation risk factor (Mueller et al., 2013) and dollar factor (Verdelhan, 2013). Although these risk factors are successful in explaining the carry trade returns, they fail to explain stock portfolio returns (e.g., Burnside, 2012). Hence, as Burnside argues, 'there is no unifying risk-based explanation of returns in these two markets'.

In this paper, I provide ample evidence in favor of the market risk-based explanation of carry trade returns. However, rather than using the traditional market beta as a risk measure, I use the *downside* market beta, the 'disaster beta' and the coskewness, which are conditional on low market returns or high market volatility. I also contribute to the debate between Lustig and Verdelhan (2007, 2011) and Burnside (2011) regarding the explanatory power of the consumption CAPM in the currency market by showing that the *downside* consumption risk of carry trades is much stronger but still insufficient to explain the cross-section of currency returns.

In a more recent study, Lettau et al. (2014) extend this analysis of the downside risk CAPM to the cross-section of currency, equity, bond and commodity portfolios. Our papers agree that the model with the downside market factor has better explanatory power than the traditional CAPM in all markets. However, our papers differ in several respects. First and most importantly, we employ different methodologies (Lettau et al. (2014) use Fama-MacBeth (1973) two-pass estimates, whereas I use GMM to estimate betas and risk premiums jointly, following the criticism in Burnside (2011)). Second, I consider alternative measures of the downside risk (the downside beta, the 'extreme' downside beta, the 'disaster beta' and the coskewness) and show that the 'extreme' downside risk measures have even higher explanatory power for the carry trades. Third, I use the global market index as a proxy for the market portfolio, whereas Lettau et al. (2014) use the US market index. Fourth, I compare the downside market factor to other currency risk factors proposed in the literature and run 'horse races'. Finally, I also separately study a period of active carry trades by institutional investors and show that all results are stronger in this period, thereby providing empirical support for the Basak and Pavlova (2013) model of the effects of institutional trading.

3.2.2. ASSET PRICING MODELS WITH DOWNSIDE RISK

3.2.2.a. THREE-MOMENT CAPM WITH BETA AND COSKEWNESS

Since currency returns are distributed asymmetrically (Brunnermeier at al., 2008), we should call for a model where the third moment is priced – the three-moment CAPM. The three-moment CAPM goes back to Kraus and Litzenberger (1976), where there is preference for systematic skewness. But for a diversifying investor, the coskewness with the market is important.

To show how coskewness enters the asset pricing equation, I lay out the three-moment CAPM of Harvey and Siddique (2000). The first-order condition for a utility-maximizing representative investor is the following standard pricing equation:

$$E_t[(1+R_{i,t+1})m_{t+1}] = 1 \quad (3.1)$$

where$R_{i,t+1}$ is the total return on asset i and m_{t+1} is the stochastic discount factor, which is equal to the marginal rate of substitution between periods t and $t+1$. To produce the three-moment CAPM, the authors assume that the marginal rate of substitution is quadratic in the market return, which can be derived by expanding the marginal rate of substitution to the second order:

$$m_{t+1} = a_t + b_t R_{M,t+1} + c_t R_{M,t+1}^2 \quad (3.2)$$

Expanding the expectation in equation (1) and substituting the expression for the stochastic discount factor (2), the authors obtain the following asset-pricing equation:

$$E_t[r_{i,t+1}] = \lambda_{1,t} Cov_t[r_{i,t+1}, r_{M,t+1}] + \lambda_{2,t} Cov_t[r_{i,t+1}, r_{M,t+1}^2] \quad (3.3)$$

where $r_{i,t+1}$ is the excess return on asset i, $r_{M,t+1}$ is the market risk premium, and $\lambda_{1,t}$ and $\lambda_{2,t}$ are functions of the expected market excess return, variance and skewness and expectation and variance of the squared market excess return. What is important is that $\lambda_{1,t}$ and $\lambda_{2,t}$ are the same across all assets, $\lambda_{1,t} > 0$ and $\lambda_{2,t} < 0$.

According to equation (3), an asset with higher covariance with the market return (higher beta) should have a higher expected return while an asset with higher covariance with the squared market return (higher coskewness) should have a lower expected return. Intuitively, adding an asset with a high coskewness to a market portfolio increases the skewness of the portfolio, and, hence, such asset is valuable and its expected return should be lower.

3.2.2.b. CAPM WITH DOWNSIDE AND UPSIDE BETAS

There are different reasons that investors may be more averse to losses than they are attracted to gains: behavioral loss aversion in the utility function (Barberis et al., 2001), rational disappointment aversion in the utility function (Ang, Chen and Xing, 2006), binding short-sale constraints (Chen, Hong and Stein, 2001), wealth constraints (Kyle and Xiong, 2001), funding liquidity constraints and liquidity spirals (Brunnermeier and Pedersen, 2009), fund flow considerations and other reasons. In such settings, assets with higher downside risk relative to their upside risk should have higher expected returns.

Ang, Chen and Xing (2006) show how the downside risk may be priced cross-sectionally in an equilibrium setting by assuming that agents have Gul's (1991) disappointment aversion utility function, which down-weights elating (above the certainty equivalent) outcomes relative to disappointing (below the certainty equivalent) outcomes. In this setting, the traditional market beta 'is not a sufficient statistic to describe the risk-return relationship of an individual stock' because agents are particularly concerned about the downside risk. The authors numerically show that the traditional CAPM alpha is increasing in the downside beta and decreasing in the upside beta. However, because the marginal utility of wealth decreases when the overall market rises, the upside risk is not as important as the downside risk. Therefore, measures of downside risk have greater explanatory power for describing the cross-section of expected returns.

3.3. DATA AND PORTFOLIO FORMATION

The data covers the period from January 1984[15] until June 2013 at a monthly frequency. The sample of countries consists of 42 developed and emerging economies. Compared with Burnside's (2012) sample of 20 countries, my sample includes many emerging market economies, some of which are popular targets of carry trades because of their high local interest rates. I also consider a sub-sample of 15 developed countries. The full list of countries is provided in the appendix.

As is common in the currency literature, I adopt the perspective of a US investor. For each country, I collect the spot and one-month forward exchange rates against the US dollar. An increase in the exchange rate means an appreciation of the respective currency against the US dollar. The exchange rate data are corrected for denominations, and periods of fixed exchange rate regimes are omitted because otherwise the currency risk would be artificially lower.

US non-durable real consumption is used to calculate the consumption risk, and the MSCI All-Country World Index (ACWI) serves as a proxy for the market portfolio. This index aggregates the stock market performance in 45 countries. I use the global stock market index rather than the US stock market index because the main carry trade investors are institutional investors investing globally[16].

The sources of data are Datastream and the Global Financial Database. I also collect monthly data on NYSE stock total returns from CRSP.

[15] A longer period from January 1974 to June 2013 is analyzed in the online appendix. Because forward prices are unavailable for such a long period, the carry trade portfolios are sorted by the nominal interest rate differential.

[16] The global market index has a correlation coefficient of 0.89 with the US stock market index, and considering the US stock market index instead does not affect the results (not reported).

Following Lustig et al. (2011), I sort currencies by the forward discount and form 5, 10 and 25 equally weighted currency portfolios to consider different levels of diversification within portfolios. The portfolios are rebalanced monthly. When the covered interest parity is satisfied, the forward discount is approximately equal to the interest rate differential. Hence, portfolio 1 always consists of currencies with the lowest local interest rates; portfolio 2 consists of the next basket of currencies in the ranking; and portfolios 5, 10 and 25 always contain currencies with the highest interest rates. Obviously, the 5 portfolios are more diversified, whereas the 25 portfolios are rather noisy. The monthly rebalancing ensures that the portfolios resemble carry trade portfolios, the composition of which changes over time as the forward discounts change.

For each level of diversification, I form HML portfolios, which have long positions in the portfolios with the highest rank (portfolios 5, 10 and 25) and short positions in the portfolios with rank 1. The HML portfolios can be considered the most aggressive carry trade strategies because they exploit the highest interest rate differentials.

For the sub-sample of developed countries, the 15 currencies are sorted by the forward discount into five portfolios. These portfolios are analyzed in section 3.4.3 and, in more detail, in section 3.5.1.

3.4. RESULTS

3.4.1. RETURN AND RISK CHARACTERISTICS OF CURRENCY PORTFOLIOS

Figure 3.1 illustrates the relationships between the average excess returns of the 10 currency portfolios sorted by the forward discount and the 10-1 HML portfolio and their traditional downside and upside betas. Here, all betas are estimated by OLS, and the downside and upside betas are estimated in the following time-series regressions using a dummy variable:

$$r_{jt} = \alpha_j + \beta_j r_{Mt} + \delta_j dummy_t * r_{Mt} + \varepsilon_{jt} \quad (3.4)$$

where r_{jt} is the return of portfolio j, r_{Mt} is the global stock market return, $dummy_t = \begin{cases} 0, r_{Mt} < 0 \\ 1, r_{Mt} > 0 \end{cases}$, β_j is the estimate of the downside beta and $(\beta_j + \delta_j)$ is the estimate of the upside beta. As defined here, the downside beta measures the sensitivity of an asset's return to the market return in states when the market return is negative. Other cut-off levels for the downside beta are considered in section 3.4.4.

Figure 3.1 shows that the spread of the downside betas (the middle panel) across portfolios is much wider than the spread in the traditional betas (the top panel), and the downside betas have much greater explanatory power in the cross-section of portfolio returns. There is an insignificant negative relationship between the upside betas (the bottom panel) and portfolio returns. The downside and upside betas do not have a symmetric relationship with portfolio expected returns, as the theoretical model of Ang, Chen and Xing (2006) predicts. Hence, separating the beta into its upside and downside components improves the validity of the CAPM in the currency market.

Table 3.1 presents the returns and various risk characteristics of the 10 currency portfolios sorted by the forward discount and the 10-1 HML portfolio[17]. The first row shows the average annualized excess returns of the portfolios. Although portfolios of higher rank appear to depreciate more against the US dollar than the lower-rank portfolios, the exchange rate depreciation does not offset the gain from the interest rate differential, as predicted by the UIP, such that the total portfolio excess returns are generally increasing with the portfolio rank. The HML portfolio, which consists of high-interest high-inflation emerging markets, generated an average return of 16.56 percent per annum during the studied period[18]. This return illustrates the profitability of carry trades.

[17] The characteristics of the 5 and 25 portfolios have the same pattern and are not reported.
[18] Returns do not account for transaction costs.

Portfolios of higher rank have higher return standard deviation and lower skewness. Although the relationship between portfolio returns and skewness is not completely monotonic, it generally confirms the findings of Brunnermeier et al. (2008).

The subsequent rows of table 3.1 show the efficient GMM estimates of consumption and the market betas of the currency portfolios[19]. The portfolio betas and beta premiums are estimated jointly by GMM using a similar system of moment conditions as in Cochrane (2005):

$$\begin{cases} E(r_{jt} - \alpha_j - b_j f_t) = 0 \\ E(r_{jt} - \alpha_j - b_j f_t) \otimes f_t = 0 \\ E(r_{jt} - b_j \lambda - \gamma) = 0 \end{cases} \quad (3.5)$$

where f_t is either a risk factor or a vector of factors, r_{jt} is the excess return on portfolio j, b_j is a factor beta, λ is a factor risk premium and γ is a constant (pricing error). The first two moments estimate the factor betas of each portfolio, and the third moment estimates the factor risk premium. I use both the efficient and identity-weighting matrices in the estimation; however, table 3.1 reports only the efficient GMM estimates, and the first-step GMM estimates are similar.

The consumption betas of all portfolios are statistically insignificant, which confirms Burnside's criticism of the relevance of the consumption CAPM for the currency market. The downside consumption betas of all portfolios are much higher and statistically significant, although the spread in them across portfolios is still insignificant to account for the cross-section of returns.

The traditional market betas are increasing with the portfolio rank from 0.11 for portfolio 1 to 0.22 for portfolio 10. All betas are statistically significant, but the spread in them across portfolios is insufficient to explain the differences in the portfolio returns.

[19] The efficient GMM estimates of betas in table 3.1 are not exactly the same as the OLS estimates in figure 3.1 because of the joint estimation of betas and beta premiums using the efficient weighting matrix. The OLS estimates are generally higher and more statistically significant. These estimates are available upon request.

The downside market betas are also monotonically increasing with the portfolio rank from -0.01 for portfolio 1 to 0.40 for portfolio 10[20]. The spread in the downside betas across portfolios is nearly four times as wide as the spread in the traditional betas. The downside betas are close to zero and statistically insignificant for portfolios 1-3; thus, these portfolios are immune to the stock market downturns and can serve as a 'safe haven'. Portfolios 9, 10 and HML, on the contrary, have high and statistically significant downside betas. Hence, these portfolios have significantly negative returns when the global stock market falls. The downside betas of these portfolios are nearly twice as high as their traditional betas. Although the average covariance of the high-interest currencies with the market is modest, it rises significantly during market downturns. Hence, carry trades tend to crash systematically along with the stock market.

Estimates of the market betas and the downside market betas in a five-year rolling window also exhibit different patterns over time. The market betas of the HML portfolio were close to zero and even negative before 2000, whereas its downside betas were usually positive, high and significant. The explanatory power of the downside market factor was high even in the beginning of the studied period, when the traditional market factor had no explanatory power at all.

Unlike the downside betas, the upside betas are decreasing with portfolio rank. When the stock market rises, low-interest currencies tend to provide higher returns than high-interest currencies. Although the upside betas of nearly all portfolios are statistically significant, they do not differ greatly.

Figure 3.2 shows the relationship between the traditional market betas, the downside betas and the upside betas of these 11 currency portfolios. Because the downside betas are increasing with the portfolio rank and the upside betas are decreasing and because the

[20] If the currencies are sorted into portfolios by their downside betas rather than the forward discounts, then a similar monotonic relationship between the downside betas and portfolio returns is observed (see the online appendix).

traditional betas are the weighted averages of the downside and the upside betas, the pattern of traditional betas across portfolios is rather flat. The traditional market betas cannot explain the returns to carry trades because they are not informative about the actual risks of the currency portfolios. By separating the traditional beta into the upside beta and the downside beta, we obtain much more information about the performance of the carry trade portfolios.

The last row of table 3.1 reports the coskewness of portfolio returns with the global stock market, which is estimated in a time series regression of returns on the squared market returns (or the market volatility factor). Similar to skewness, coskewness is positive and statistically significant for portfolio 1, is monotonically decreasing with the portfolio rank, and is negative and significant for the high-interest portfolios. A significant negative coskewness indicates that a portfolio has negative returns in periods of high stock market volatility, and investing in such a portfolio increases the crash risk for investors. The same conclusion has been drawn by Menkhoff et al. (2012a), Christiansen et al. (2011) and Clarida et al. (2009) in examining conditional currency returns using different proxies for volatility. However, coskewness as a measure of volatility risk has not been analyzed previously in the currency literature.

The coskewness and the downside beta can be considered alternative measures of the downside market risk because high stock market volatility is typically observed on the downside. The downside betas are strongly correlated with the coskewness across portfolios (the correlation coefficient is -0.999), and both are statistically significant in multifactor setting (see the online appendix for the multifactor specifications and 'horse races' between alternative risk factors).

Overall, table 3.1 suggests that the high returns to carry trades is compensation for their high downside market risk, which cannot be diversified away because the global market portfolio performs poorly in such states.

3.4.2. DOWNSIDE RISK PRICING IN THE CURRENCY MARKET

In this section, I test the validity of alternative asset pricing models for the cross-section of 10 currency portfolios of developed and developing countries sorted by the forward discount and the 10-1 HML portfolio. I consider the following models: the consumption CAPM, the CAPM with the downside consumption beta, the traditional CAPM, the downside beta CAPM, the upside beta CAPM and the coskewness CAPM.

The models are estimated by GMM using the moment conditions in (5). GMM minimizes the weighted sum of these moments, and the covariance matrix between the two sets of moments captures the effect of generated regressors on the standard errors of the risk premiums. The GMM estimation is preferable to the Fama-MacBeth two-step procedure, because following the latter we are more likely to falsely accept the model due to generally lower standard errors of risk premiums.

For each specification, I estimate both the first-step GMM with the identity weighting matrix and the iterated GMM with the efficient weighting matrix, which assigns more weight to moments that are estimated more precisely.

The GMM estimates of the risk premiums and the various fit statistics for the alternative specification are reported in table 3.2.

First, the consumption CAPM is rejected on all grounds. Not only are the consumption betas in table 3.1 insignificant, but all consumption beta premiums are statistically insignificant (as in Burnside, 2011). The consumption CAPM with the downside consumption betas performs better in terms of the overall fit of the model, but the downside consumption risk premiums are still statistically insignificant. Non-durable consumption is not sufficiently volatile for the consumption betas to be measured precisely, and consumption betas cannot account for the cross-sectional spread of carry trade returns.

Second, the traditional CAPM and the upside beta CAPM do not perform well. Both models are rejected by the J-statistics in the case of the identity weighting matrix. The market risk premium is economically too high and statistically insignificant in the case of the identity weighting matrix. The upside beta premium is even negative. This result is consistent with the Ang, Chen and Xing (2006) model, which predicts that in good states of the world, the marginal utility of wealth is low, and assets that perform well in such states are not particularly valuable.

Third, the downside beta premiums and the coskewness premiums are all highly statistically significant and have the correct signs, all intercepts are close to zero and the models are not rejected by the J statistics. The downside beta CAPM wins the ‘horse race’ because it has the lowest J-statistics and the lowest mean sum of squared errors (MSSE) and hence a better overall fit.

As Lewellen, Nagel and Shanken (2010) note, to make the correct judgment about an asset pricing model, we must consider not only the statistical significance of risk premiums but also their magnitude and economic meaning. Whereas the estimates of the traditional beta premium are 13-17 percent per month, the estimates of the downside beta premium are 3-4 percent per month. The estimates of the coskewness premium are minus 0.5-0.6 percent per month. Such estimates for the downside beta and coskewness premiums make economic sense. For example, if we multiply them by the downside beta and coskewness of the HML portfolio in table 3.1 (0.4 and -2.41, respectively) and annualize, then the expected excess return for this portfolio is approximately 16-17 percent per annum. The actual average annual excess return on this portfolio was 16.56 percent during 1984-2013. It follows that the high returns to carry trades were simply compensation for their high downside market risk.

Lustig et al. (2011) propose two factors – EW (level) and HML (slope) – to explain the returns to currency portfolios. The authors show that currency portfolios sorted by the forward discounts load differently on the HML factor and that the spread of these loadings accounts for the spread of the portfolio returns. However, the HML portfolio itself has high loading on the downside market factor. For example, the HML strategy considered in this paper (10-1 portfolio) has a downside beta of 0.4 and is highly statistically significant. Because higher-interest currency portfolios load more on the downside market factor, they load more on the HML factor. The two factors are closely linked, and their explanatory power in the cross-sectional regressions is similar. See the online appendix for the 'horse races' between alternative factors.

My findings are inconsistent with Burnside's (2012) claim that the stock market risk cannot explain the returns to carry trades. He argues that the market betas of carry trade portfolios are too small to rationalize their high returns, and once a traditional market-risk-based model is estimated for currency and stock portfolios together, it is rejected because of high pricing errors for the currency portfolios. However, Burnside's sample of countries is much smaller than mine. Even my OLS estimates of the market betas are higher because my sample includes more emerging countries, which are riskier. Moreover, when I measure the market risk on the *downside*, it is higher for the high-interest currencies and lower for the low-interest currencies; thus, the spread is much wider. The OLS downside beta of my HML portfolio is 0.48[21]. Therefore, the market risk of carry trades is more than twice as high when measured on the downside.

In the cross-sectional tests, Burnside estimates the models for 25 Fama-French stock portfolios and two currency portfolios. Even in the case of the identity weighting matrix, the weight of the stock portfolios is much higher (25/27) than the weight of the currency portfolios (2/27) in the estimation. Therefore, the models are in fact estimated for the stock portfolios, and he then determines whether the currency portfolios 'fit' these models. Because the Fama-French portfolios can be priced by the Fama-French factors, not surprisingly, he finds that the Fama-French model is the only model that is not rejected. However, why would the size and value factors price the currency portfolios? These factors would not do so, and he

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[21] The OLS estimates are only shown in figure 3.1. They are available upon request.

finds that the pricing errors are significant indeed[22]. Burnside concludes that 'there is no unifying risk-based explanation of returns in these two markets'. I show that the asset pricing models with downside market risk fit the cross-section of currency portfolio returns well. In the next section, I estimate the same models for the currency and downside-beta-sorted stock portfolios jointly, and I arrive at the same conclusion.

3.4.3. COMPARISON OF CURRENCY AND STOCK MARKETS

Is the downside risk priced similarly in the currency and stock markets? The efficient GMM estimate of the downside risk premium is approximately 4 percent for the 10 currency portfolios of developed and developing countries. Regarding the evidence from the stock market, Ang, Chen and Xing (2006) estimate the downside beta premium at between 2.8 and 6.9 percent (statistically significant) in the Fama-MacBeth (1973) regressions for individual NYSE stock returns during 1963-2001. But the Fama-MacBeth estimates are not directly comparable to the efficient GMM estimates. Therefore, I estimate the market risk premiums for currency and stock portfolios jointly using GMM.

Rather than considering the Fama-French stock portfolios, as in Burnside (2012), I consider stock portfolios sorted by the downside beta because these portfolios have a clear downside risk-return relationship, whereas other risks are diversified away within the portfolios. Following Ang, Chen and Xing (2006), I restrict the sample to NYSE stocks to minimize the illiquidity effect of small firms[23]. Stocks with fewer than 60 time series observations are excluded. This filter leaves 3,349 stocks in the sample.

Every month, all stocks are sorted by their downside betas, estimated in a five-year rolling window prior to the sort date, into five equally weighted portfolios. Portfolio 1 always contains 20 percent of the stocks with the lowest pre-ranking downside betas, and portfolio 5

[22] The efficient GMM makes the 'fit' of the currency portfolios even worse because it attaches an even higher weight to the stock moments that are measured more precisely.

[23] Ang, Chen and Xing (2006) show that the validity of the downside beta is confirmed in a wider sample of NYSE, AMEX and NASDAQ firms.

contains 20 percent of the stocks with the highest downside betas. Because the number of stocks in the sample is large, all portfolios are highly diversified, and this sorting procedure allows a focus on the downside risk of portfolios.

I consider two sets of currency portfolios sorted by the forward discount. The first set includes five currency portfolios for developed and developing countries. These portfolios are formed from the same currencies as in the previous section, but they are more diversified. On average, each portfolio consists of seven currencies. The second set of five portfolios is formed from currencies of developed countries only. Each portfolio consists of three currencies, on average.

I estimate alternative asset pricing models for five currency and five stock portfolios together[24] using the moment conditions (5). It is important to have the same number of currency and stock portfolios in the estimation to ensure that the first-step GMM treats currencies and stocks equally a priori. The efficient GMM will then amend the weights based on asset-pricing considerations.

Table 3.3 reports the efficient GMM estimates of risk premiums and various test statistics for the downside beta CAPM, the coskewness CAPM and the traditional CAPM for five currency and five stock portfolios. The first-step GMM estimates are similar and are not reported.

Regardless of which set of currency portfolios is used (all countries or developed countries only), the results are similar. The downside beta premium, the traditional beta premium and the coskewness premium are all highly statistically significant. None of the models is rejected by the test for overidentifying restrictions. The MSSE for the currency moments are even lower than those in table 3.2. Hence, adding stock portfolios does not worsen the fit of the models. However, the MSSE for the stock moments are all higher because of the generally higher volatility of stock returns. The downside beta CAPM and the

[24] I also estimated the models for 10 currency and 10 stock portfolios, sorted in the same manner. The results are similar and are not reported.

coskewness CAPM have lower J statistics and MSSE than the traditional CAPM and are thus superior for both currency and stock portfolios.

The downside beta premium estimated for the currency and stock portfolios jointly (1.69 percent in table 3.3) is lower than the downside beta premium estimated for the currency portfolios alone (3.96 percent in table 3.2), and the coskewness premium is also lower by the absolute value. Although the downside risk *is* priced in both markets, the price of risk appears to be higher in the currency market. This outcome may be a consequence of underpricing currencies of high-interest emerging economies. These currencies have overly high returns relative to their downside betas and drive the downside beta premium upward[25]. Indeed, if we restrict the sample to currencies of developed countries, the estimate of the downside beta premium obtained for these currency and stock portfolios is lower (0.93 percent in table 3.3). The downside beta premium estimated for the developed countries' currency portfolios alone is also lower (a more detailed analysis of currencies of developed countries is presented in the online appendix).

Figure 3.3 plots the downside risk-return relationship for five currency (triangles) and five stock (round dots) portfolios. The currencies of all countries are plotted in the top panel, and the currencies of developed countries are plotted in the bottom panel. We observe that portfolio C5 in the top panel, which consists of currencies of high-interest emerging markets, is an outlier. Once we exclude this portfolio or restrict the sample of currencies to developed countries, the currency and stock portfolios lie closely to the security market line with high R^2 in the case of both the downside beta CAPM and the coskewness CAPM.

Overall, the currency portfolios have lower downside risk (lower downside betas and higher coskewness) and lower expected returns than the stock portfolios, but the downside

[25] Why do capital flows not eliminate this underpricing? These countries have high country risk (e.g., measured by the Fitch sovereign rating). Substantial uncertainty is associated with investments in these currencies; in some cases, there were (are) explicit or implicit capital controls and insufficient liquidity. Institutional investors may establish country limits to prevent position-taking in the currencies of high-risk countries; hence, country risk is a natural limit to arbitrage. Menkhoff et al. (2012b) find that high country risk may explain why arbitrageurs do not also fully exploit high currency momentum returns.

risk premiums in the currency and stock markets are similar, except for the currencies of high-interest emerging economies, which provide a higher premium. I cannot formally reject the hypothesis that the downside market risk is priced similarly in the two markets.

Is a risk premium of 1-2 percent per month *fair* compensation for the downside risk? According to the traditional CAPM, the expected market excess return is fair compensation for the overall market risk. According to Kahneman and Tversky's (1979) prospect theory, people are approximately 2.5 times more averse to losses than to gains, and we may therefore expect the downside risk premium to be approximately two times higher. Because the market excess return was approximately 6 percent per annum during the studied period, the fair downside risk premium should be approximately 15 percent per annum.

Another approach to identify the fair downside risk premium is to construct the downside market factor-mimicking portfolio. The risk price of the factor should be equal to the mean return on this traded portfolio to satisfy the no-arbitrage condition. I follow the two-step methodology of Breeden et al. (1989) and Menkhoff et al. (2012a). First, I regress the downside market factor on the five currency portfolio excess returns and obtain the betas[26]. I then use the betas as the weights of the currency portfolios to construct the factor-mimicking portfolio. The average annual return to this factor-mimicking portfolio is 11 percent.

The two approaches suggest that the fair downside risk price is approximately 1 percent per month, which is what I find in the cross-section of developed currencies and stock portfolios. Therefore, the high returns to carry trades are *fair* compensation for their high downside market risk. However, the currencies of emerging markets provide a higher risk premium, perhaps because of other risks involved.

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[26] These betas are monotonically increasing in the portfolio rank.

3.4.4. EXTREME DOWNSIDE RISK AND DISASTER RISK

In the previous sections, the downside betas are estimated conditional on the negative market return. In this section, I use different cut-off levels for downside betas to examine the behavior of carry trades in more extreme market conditions.

I use the following alternative dummy variables to estimate downside betas:

$$dummy1_t = \begin{cases} 0, r_{mt} < \mu \\ 1, r_{mt} > \mu \end{cases}$$

$$dummy2_t = \begin{cases} 0, r_{mt} < \mu - 0.5\sigma \\ 1, r_{mt} > \mu - 0.5\sigma \end{cases}$$

$$dummy3_t = \begin{cases} 0, r_{mt} < \mu - \sigma \\ 1, r_{mt} > \mu - \sigma \end{cases}$$

$$dummy4_t = \begin{cases} 0, r_{mt} < \mu - 1.5\sigma \\ 1, r_{mt} > \mu - 1.5\sigma \end{cases}$$

whereμ is the mean global market return and σ is the return standard deviation. The downside beta, estimated with dummy 4, for example, shows the normalized covariance with the market subject to the market return being below its mean by 1.5 standard deviations. This downside beta is the most ‘extreme’ because it shows an asset’s performance in the worst states of the world – in the states of stock market crashes.

I also construct a disaster dummy to measure ‘disaster betas’ – market betas in times of different disasters. Ranaldo and Söderlind (2010) create a list of economic, political and natural disaster events using a news search, and they study the performance of several major currencies on these dates. Economic disasters include famous financial crises, defaults or bankruptcies; political disasters include wars, terrorism and bombings; and natural disasters include hurricanes, tornados, tsunamis and earthquakes. The full list of disasters is provided in the appendix.I use their list to create a disaster dummy that is equal to zero in the month in which a disaster occurs and one otherwise:

$$disaster\_dummy_t = \begin{cases} 0, disaster \\ 1, no\_disaster \end{cases}$$

Table 3.4 reports the efficient GMM estimates of the 'extreme' downside betas and 'disaster betas', estimated with dummy 4 and the disaster dummy, respectively (panel A)[27], as well as the estimates of the alternative downside beta premiums and the 'disaster beta' premium (panel B).

The 'extreme' downside betas are all higher than the downside betas in table 3.1, and they are all highly statistically significant. The 'disaster betas' are even higher. Therefore, the carry trades perform disproportionally worse in times of stock market crashes or disasters. However, even the low-interest currency portfolios have statistically significant 'disaster betas'. Hence, all currencies generally depreciate against the US dollar during global distress, which confirms the 'safe haven' properties of the US dollar as a reserve currency, as documented by Maggiori (2013).

Turning to panel B, all downside beta premiums and the 'disaster beta' premium are highly statistically significant and are higher if we consider more adverse market conditions. All specifications have similar test statistics. The intercepts are statistically significant in the cases of dummy 4 and the disaster dummy, reflecting the 'safe haven' properties of the dollar in times of extreme stock market downturns or economic, political or natural disasters. This intercept reflects the 'dollar safety premium'.

Overall, the results do not change when I vary the cut-off level for the downside beta and consider the 'disaster beta' as an alternative downside risk measure. Carry trades perform even worse in extreme stock market conditions, and high returns to carry trades serve as compensation for this poor performance.

[27] The downside betas estimated with dummies 1, 2 and 3 are similar to those in table 3.1 and are not reported.

3.5. ROBUSTNESS TESTS

3.5.1. SUB-SAMPLE OF DEVELOPED COUNTRIES

I study a sub-sample of developed countries separately for two reasons. First, some of the emerging countries may not have had a sufficiently liquid futures market in the earlier years, or some currencies were pegged to the US dollar, hence with artificially lowered exchange rate risks. Therefore, the downside beta premium obtained for the entire sample may be overestimated. Second, the most popular carry trade currencies are still the currencies of developed countries, and institutional investors limit their exposure to emerging markets despite their high returns. Again, the downside risk premium obtained for the entire sample may be higher than in other markets because of such limits to arbitrage. Easily accessible currencies of developed countries are better test assets for a comparison of the currency and stock markets, as shown in section 3.4.3.

Table 3.5 presents the return and risk characteristics of five currency portfolios of developed countries (panel A) and the efficient GMM estimates of various risk premiums (panel B). Portfolios of higher rank have higher returns and return standard deviations and lower (negative) skewness. The efficient GMM estimates of the consumption betas and the downside consumption betas are all statistically insignificant. Moreover, both the consumption beta premium and the downside consumption beta premium are statistically insignificant. There is no evidence that the consumption risk can explain the cross-section of these currency portfolio returns.

All global stock market betas (the traditional beta, the downside beta, the 'extreme' downside beta, the 'disaster beta' and the upside beta) are monotonically increasing with portfolio rank from close to zero and insignificant values for portfolio 1 to rather high and significant values for portfolio 5. The spread in the market betas across the portfolios is highly significant. Examining the 5-1 HML portfolio, we observe that its market beta is 0.18, its downside beta is 0.27, its 'extreme' downside beta is 0.29 and its 'disaster beta' is 0.40.

These betas are lower than those of the 10-1 HML portfolio, except for the ‘disaster beta’. The ‘disaster beta’ is higher here because portfolio 1 of currencies of developed countries has a lower ‘disaster beta’ than portfolio 1 of all currencies. In times of economic, political and natural disaster, all currencies generally depreciate against the US dollar, except for the low-interest currencies of developed countries (e.g., the Japanese yen or the Swiss franc). Therefore, the US dollar and the low-interest currencies of other developed countries possess ‘safe haven’ properties (as in Ranaldo and Söderlind, 2010). However the ‘disaster betas’ of the high-interest currencies of developed countries are comparable in magnitude to the ‘disaster betas’ of high-interest currencies of developing countries. Hence, regardless of which sample of currencies we consider, carry trades crash during periods of disaster or significant stock market downturns.

In panel B, the traditional beta, the downside beta, the ‘extreme’ downside beta, the ‘disaster beta’ and the coskewness premiums are all statistically significant, are lower in absolute values than in the case of all currencies and are similar to the premiums obtained for the stock market. The downside beta premium is between 1 and 2 percent per month, and the coskewness premium is -0.4 percent per month. The downside beta CAPM, the ‘extreme’ downside beta CAPM and the ‘disaster beta’ CAPM have the lowest J-statistics and MSSE and are therefore again superior to other models.

3.5.2. PERIOD OF ACTIVE CARRY TRADES BY INSTITUTIONAL INVESTORS: 2000-2013

The early 1990s were years of soaring interest rates, capital controls, political instability and related currency crashes in several emerging countries in the sample. This turmoil was reflected in the extreme behavior of the top portfolios, such as their high returns and negative skewness. At the end of 1990s, after the financial crises in East Asia and Russia, the economic situation in most emerging countries stabilized. We observe a tremendous growth of carry trade activity that began in the late 1990s (Galati et al., 2007). This growth was supported by huge inflows of assets under management of hedge funds, the main carry trade investors (Jylhä and Suominen, 2011).In this section, I study the latest period from January 2000 until June 2013 – the period of active carry trades.

Table 3.6 reports the return and risk characteristics of 10 portfolios of all currencies and five portfolios of currencies of developed countries (panel A) as well as the efficient GMM estimates of risk premiums for the two sets of portfolios (panel B).

All market betas and coskewness values are highly statistically significant in the recent period. All currencies strongly co-vary with the global stock market, especially on the downside, which can actually be a consequence of active institutional trading in currencies during the last decade, as the model of Basak and Pavlova (2013) predicts. The market betas, the downside betas and the 'disaster betas' of the high-interest portfolios are even higher now.

The increase in the market betas is greater for the high-interest portfolios of developed countries, particularly if we consider the 'extreme' downside betas (0.46 versus 0.28). The coskewness of portfolio 5 also decreased significantly from -0.18 to -1.37 and became significant. A carry trade strategy that involved only developed countries had significantly higher downside market risk in 2000-2013. In fact, regardless of which set of currencies we consider, the carry trade long-short portfolios have similar downside market risk, whereas the downside risk of currencies of emerging markets was previously much higher. High-interest currencies of developed and developing countries tend to crash equally in states of adverse stock market conditions or political and natural disasters. This behavior is evidence of the 'asset-class effect' in the currency market, as these currencies are the most popular target currencies of carry traders. Basak and Pavlova (2013) provide theoretical explanation that the assets that institutions trade exhibit a greater degree of co-movement than other traded assets.

As before, the spread in the downside betas is wider than the spread in the traditional betas across both sets of portfolios, and the spreads in the 'extreme' downside beta and ‘disaster betas’ are even wider. All risk premiums are similar and highly significant, and all models perform equally well in the recent period. However, the traditional CAPM has the highest J-statistics and MSSE and hence performs worse.

The estimates of the downside beta premiums obtained for the entire sample of currencies are higher than the estimates obtained for the sub-sample of currencies of developed countries, although the differences are less significant. The price of downside risk is higher for the currencies of emerging markets, perhaps because of the limits that institutions set for their exposure to emerging markets. Such limits and the high sovereign risk of these countries prevent capital flows from arbitraging away the excess returns in the emerging markets.

3.5.3. ‘HORSE RACES’ BETWEEN ALTERNATIVE RISK FACTORS

In this paper I claim that the downside market factor (or the downside beta) and market volatility factor (or the coskewness) both can explain the cross-section of carry trade returns well. The two factors are highly correlated (the correlation coefficient is -0.71) and it is difficult to separate their effects, because high market volatility is usually observed on the downside. Therefore, I consider the both factors as the downside risk factors.

Among other risk factors which have proved to have high explanatory power for carry trades are the Lustig et al. (2011) HML factor and the Menkhoff et al. (2012a) global currency volatility innovation factor. These two factors are derived from currency returns themselves and are both highly correlated with the second principal component of carry trade portfolios, which is shown to explain a great proportion of currency return variance.

In this section, I ran ‘horse races’ between the four alternative factors in one-factor and multifactor settings. I use my own HML factor, which is a little bit different from the Lustig et al. (2011) HML factor due to the different samples of countries, and I use Menkhoff et al. (2012a) currency volatility factor (VOL).

First of all, the currency factors (HML and VOL) are not highly correlated with the downside market factor and the market volatility factor (the correlation coefficient is 0.35-0.39 by the absolute value). The second principal component (which together with the first principal component explains 91% of variance) has the highest correlation with the HML factor[28] and the lowest correlation with the VOL factor. The market factors are in between.

I also construct the factor-mimicking portfolios for the downside market factor, the market volatility factor and the currency volatility factor by regressing each factor on the five currency portfolio returns, and using the obtained betas as the weights of the currency portfolios in the factor-mimicking portfolios. Interestingly, the three factor-mimicking portfolios are almost perfectly correlated (the correlation coefficient is 0.99 by the absolute value), because the currency portfolios load similarly on the factors (portfolio 1 has the lowest loading on the factors and portfolio 5 has the highest loading). The second principal component correlates similarly with the three factor-mimicking portfolios.

Table 3.7 reports the efficient GMM estimation results for the five portfolios of all currencies[29]. In columns 1-4 I compare one-factor models. All four factors are highly statistically significant, their premiums have the correct signs, and none of the models is rejected by the J-statistics. So, all factors are doing well in explaining the currency returns. But the model with the downside market factor has the lowest MSSE and J-statistics and hence has the lowest pricing errors.

In columns 5-9 I consider two-factor specifications and in columns 10-11 three-factor specifications. When both the downside market factor and the market volatility factor are included (column 5), none of them loses the statistical significance. Since the two factors are highly multicollinear, it is difficult to disentangle their effects. The downside beta and coskewness premiums are the same as in the one-factor specifications.

[28] This is not surprising given that they are constructed in approximately the same way.

[29] The results for the 10 portfolios of all currencies, for the 5 portfolios of currencies of developed countries, and for the 5 currency and 5 stock portfolios are similar.

When I consider the downside market factors and the VOL factor (columns 6, 8 and 10), the downside market factors remain significant while the VOL factor does not. The VOL premium shrinks dramatically. Whereas the VOL factor alone can explain the carry trade returns, its explanatory power is swiped off by the downside market factors. Menkhoff et al. (2012a) provide ample evidence in favour of their currency volatility factor, but they never control for the market factors in their specifications. It turns out, that the downside market factors are superior in explaining currency returns.

When I consider the downside market factors and the HML factor (columns 7, 9 and 11), the HML factor remains significant, while the downside market factor and the market volatility factor become insignificant[30]. Menkhoff et al. (2012a) also find that the VOL factor becomes insignificant when they control for the HML factor. So, the HML factor has the highest appeal to explain the currency returns. But the HML factor is not “exogenous” to these portfolios, it is constructed form these portfolios in the first place. Therefore, it is not surprising that it has such a high explanatory power.

Unfortunately, the HML factor cannot be considered as a unifying risk factor because it does not explain returns to stock portfolios. Table 3.8 shows the efficient GMM estimates for the 5 stock portfolios sorted by the downside betas. Although none of the factors is rejected by the J-statistics, only the downside market factor and the market volatility factor are statistically significant, and their premiums are the same as in the currency market. The HML and the VOL factors do not have significant explanatory power in the stock market. Burnside (2012) also finds that the HML factor (and other currency factors) cannot explain the returns to the 25 Fama-French portfolios sorted on size and value.

While the currency factors (HML and VOL) have high explanatory power in the currency market, they have low explanatory power in the stock market. But the downside market factors have high explanatory power in the both stock and currency markets. Lettau et

[30] The same holds if the factor-mimicking portfolios are used instead of the factors themselves.

al. (2014) also show the validity of the downside market risk in the bond and commodity markets. The downside market factors also have theoretical grounds, as discussed in section 3.2.2. Therefore, the downside market risk wins the 'horse race' and can be considered as a unifying explanation of returns in various asset markets.

3.5.4. DOWNSIDE BETA SORT

If the downside beta is an appropriate risk measure, then sorting currencies into portfolios by their downside betas would result in a monotonic risk-return relationship. Currencies with higher downside betas should provide higher expected returns.

In this section, instead of looking at carry trade portfolios, sorted by the forward discount, I look at currency portfolios, sorted by their downside betas, which are estimated in a 5-year rolling window prior to the sort date. The first set of downside betas is estimated during the period from January 1984 until December 1988, and the first sort is done in January 1989. Then the window moves by one month forward, and the procedure is repeated. All currencies are assigned to five portfolios. Generally, these portfolios are similar to the carry trade portfolios, although not exactly the same.

Table 3.9 reports the return and risk characteristics of these portfolios. As expected, portfolios with higher downside beta yield higher excess returns. Although I sort by the downside betas, all market betas and the coskewness of these portfolios exhibit monotonic patterns. The market beta ranges from 0.13 to 0.26, the downside beta ranges from 0.15 to 0.41, the 'extreme' downside beta ranges from 0.20 to 0.44, the 'disaster beta' ranges from 0.21 to 0.43, and the coskewness ranges from -0.62 to -1.66. The spread in the market betas across the portfolios is the smallest, the traditional market risk premium is insignificant (panel B), and the CAPM has the highest MSSE. But all downside risk premiums are statistically significant, and their estimates are similar to the estimates for carry portfolios and economically meaningful. The downside beta premium is about 2 percent per month and the coskewness premium is about -0.5 percent per month. This test confirms that the downside risk is priced in the currency market.

3.5.5. LONG TIME SERIES OF DATA: 1974-2013

In this section, I study the longest period from 1974 until 2013. This period starts after the break down of the Bretton Woods system. Since the forward prices are not available for such a long period, the currency portfolios are sorted by the nominal interest rate differential. I use 3-month Treasury bill rates or rates of comparable instruments for all countries (developed and developing), for which data is available. If the covered interest parity is satisfied, the interest rate differential should be approximately equal to the forward premium, and the two alternative sorts should produce similar currency portfolios.

Table 3.10 reports the risk premiums obtained for 10 interest rate sorted currency portfolios. The results have hardly changed. The consumption risk premium and the traditional market risk premium are insignificant, and the both models have high MSSE. The CAPM and the upside beta CAPM are rejected by the J-statistics (at 10% significance level). The downside beta premium, the 'extreme' downside beta premium and the coskewness premium are statistically significant and similar in magnitude to the premiums obtained for 1984-2013. Inclusion of 10 years of data did not affect the results.

Moreover, if we look at the dynamics of 5-year rolling betas of the HML currency portfolio, the downside betas were always high while the traditional betas were not. Therefore, the traditional CAPM had no explanatory power in the beginning of the period while the downside beta CAPM always explained the cross-section of currency returns.

3.5.6. TIME-VARYING MARKET BETAS AND FAMA-MACBETH ESTIMATION

While in the previous sections betas were assumed constant in the sample, in this section, I allow betas to vary over time. I follow the two-step Fama-MacBeth (1973) procedure where, in the first step, betas are estimated in a five-year rolling window, and in the second step, the cross-sectional regression of portfolio returns on betas in the preceding five years is estimated. Hence, this is an out-of-sample test. I concentrate on the latest period from January 2000 until June 2013 when the stock market risk of currency portfolios seems to be more important. Since the first set of betas is estimated during the period from January 1995 until December 1999, the first cross-sectional regression is run for January 2000. Then the rolling window moves by one month and the procedure is repeated. This generates a time series of beta premiums, from which I find the average beta premium and its statistics.

Lustig and Verdelhan (2011) find significant time variation of betas of their currency portfolios, with betas increasing dramatically during crisis periods. I also find some variation in the estimated upside and downside betas over time, although the overall pattern is more monotonic (generally, all stock market betas have monotonically increased over time in the studied period). The variation in the downside betas is much lower than the variation in the traditional market betas.

The cross-sectional relationship of time-varying betas of 10 currency portfolios of developed and developing countries is the same as before. The lowest-interest currency portfolio downside beta is always negative with the average value of -0.06 and little time variation. The downside beta of the highest-interest portfolio is always the highest in the cross-section with the average value of 0.54 and the maximum and minimum values of 0.76 and 0.16, respectively (OLS estimates). The downside betas of all portfolios, except portfolio 1, increased significantly during the financial crisis in 2008-2009, when carry trades crashed dramatically. There is a particularly visible positive relationship between portfolio rank and the downside beta in this period.

In the Fama-MacBeth cross-sectional regressions for 10 currency portfolios, the downside beta premium is 12 percent per annum with a t-statistic of 2.12, while the upside beta premium is -0.02 and insignificant, as before. The two betas explain 45 percent of portfolio excess returns, on average, while the traditional beta explains only 32 percent of returns. Generally, the conclusion that the downside market risk can explain the returns to carry trades is robust when betas are time-varying and premiums are estimated by OLS.

3.6. CONCLUSION

In this chapter, I examine the global downside market risk of currencies as an explanation for the high excess returns to carry trades. These excess returns have been consistently observed empirically and led to the growing popularity of carry trades among both institutional and private investors.

I consider three alternative measures of downside risk (the downside beta, the 'disaster beta' and the coskewness) and show that these measures have high explanatory power.I find that the downside market risk of currency portfolios is monotonically increasing in the local interest rate level. The returns of high-interest (investment) currencies have high downside stock market betas and 'disaster betas' and significant negative coskewness with the stock market; by contrast, the returns of low-interest (funding) currencies have insignificant downside betas and positive coskewness. This finding suggests that returns to carry trades are asymmetrically distributed with a high crash risk and that the crashes occur exactly in the worst states of the world, with declining stock markets and a high marginal utility of wealth.

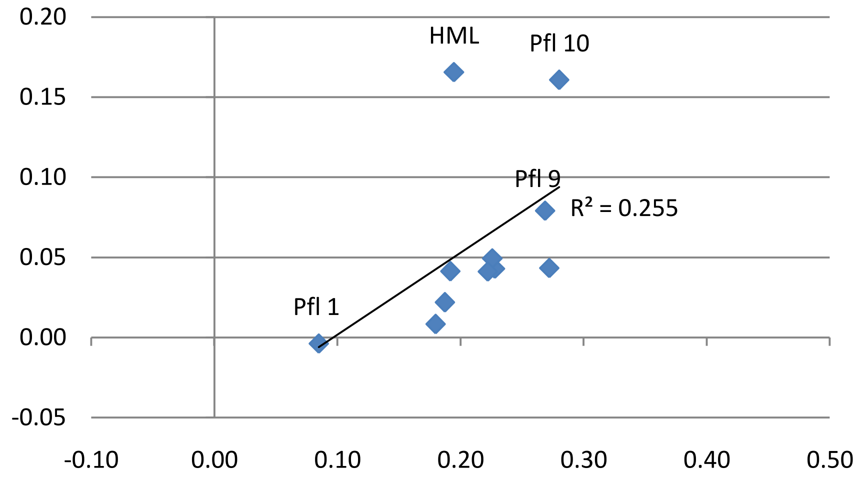
The downside market beta and the coskewness have much greater explanatory power than the traditional market beta in the cross-section. The GMM estimates of the downside beta and coskewness premiums are highly significant, similar in the currency and stock markets and close to the theoretical values. The downside risk is priced similarly in different markets, and the high returns to carry trades are *fair* compensation for their high downside market risk.

The results are robust to the use of different sets of currency portfolios and different methods of estimation, and they are even stronger if we consider the 'extreme' downside risk and disaster risk or the latest period of active carry trades[31]. The downside risk of investment currencies is even higher in the recent period, regardless of whether these currencies belong to developed or developing countries, and the explanatory power of the downside risk in the cross-section is greater. This result suggests that there is a closer link between the currency and stock markets today. The increasing volume of carry trade activity by institutional investors may have contributed to this trend. According to the Chairman of UK'sFinancial Services Authority, Adair Turner, the carry trade can be destructive to some economies: 'if the trades were reduced, the world would be a better place'[32].

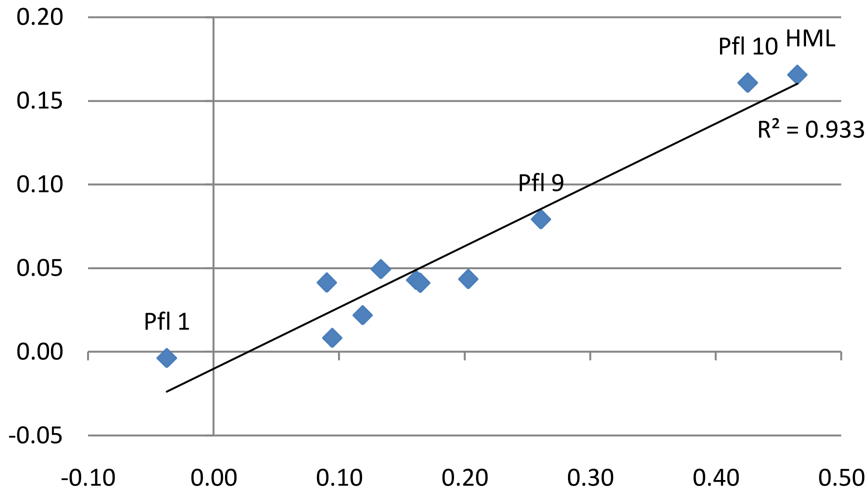
[31] The analysis of the recent period is provided in the online appendix.
[32] "Davos: FSA chief turns on 'valueless' carry trade", The Times, 30 January 2010.

Figure 3.1. Risk-return relationship for 11 currency portfolios (all countries)

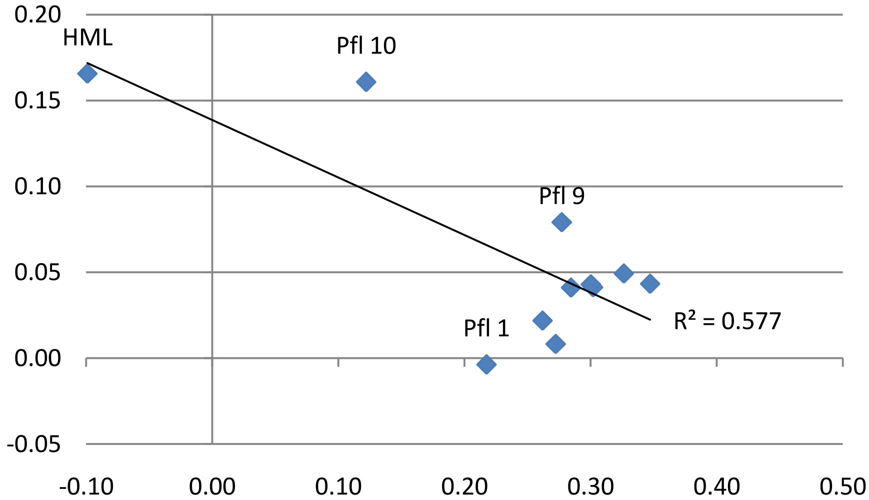
Return VS Beta



Return VS Downside beta

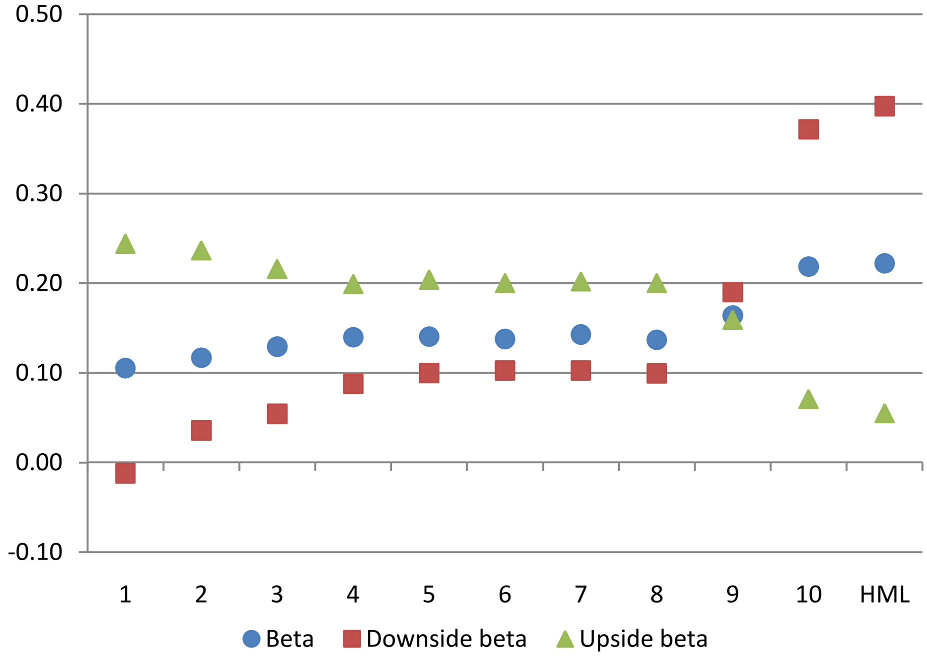


Return VS Upside beta



Note: The figures show average annualized portfolio excess returns (on the vertical axis) and the global market betas (on the horizontal axis) of 10 currency portfolios, sorted by the forward discount, and the HML portfolio. The betas are estimated by OLS. Jan 1984 – June 2013.

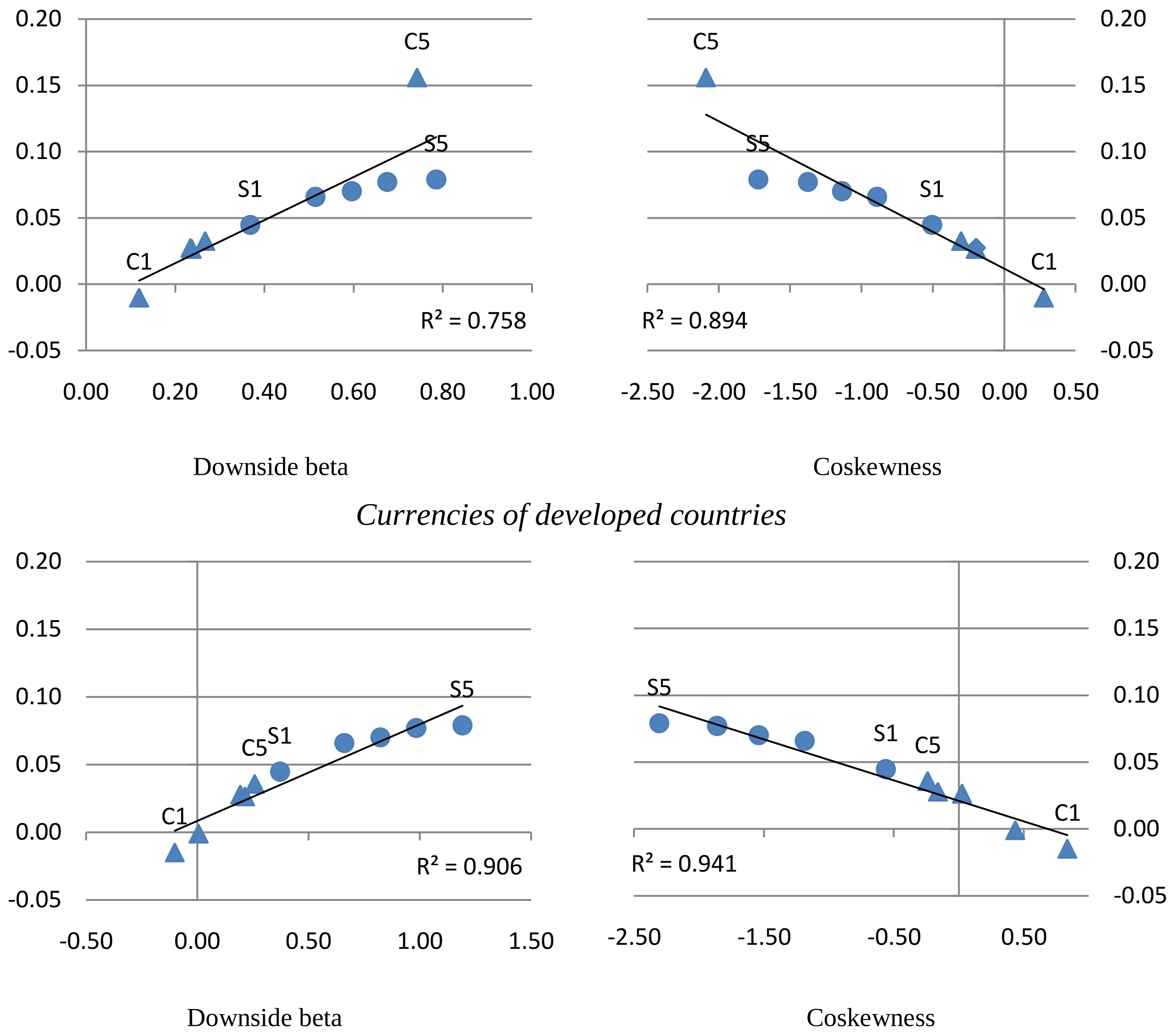
Figure 3.2. Betas, downside betas and upside betas of 10 carry trade portfolios and the 10-1 HML portfolio (all countries)



Note: The figure shows the efficient GMM estimates of the global market betas, downside betas and upside betas (on the vertical axis) of 10 currency portfolios, sorted by the forward discount, and the HML portfolio.

Figure 3.3. Downside risk-return relationships for currency and stock portfolios

Currencies of all countries



Note: Average portfolio excess returns on the vertical axis, downside betas and coskewness on the horizontal axis. Triangles represent currency portfolios, sorted monthly by the forward dicount (all countries in the top panel, developed countries in the bottom panel). Round dots represent stock portfolios, sorted monthly by the downside betas, which are estimated in a 5-year rolling window prior to the sort date. Downside betas and coskewness of the currency and stock portfolios are estimated jointly by the efficient GMM.

Table 3.1. Return and risk characteristics of currency portfolios

The table reports return and risk characteristics of 10 currency portfolios, sorted by the forward discount, and the 10-1 HML portfolio. The portfolios are rebalanced monthly. All returns are annualized and expressed in absolute values. The reported betas and coskewness are the efficient GMM estimates. The global market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. Jan 1984 – June 2013.

	Pfl 1	2	3	4	5	6	7	8	9	Pfl 10	HML
Annualized excess return (%)	-0.37	0.83	2.19	4.12	4.29	4.93	4.11	4.34	7.91	16.07	16.56
St. deviation (%)	21.85	27.96	30.49	28.89	31.69	32.49	31.86	36.29	35.00	39.52	41.27
Skewness	0.03	0.07	-0.26	-0.05	-0.32	0.06	-0.33	-0.80	-0.99	-0.69	-0.59
Kurtosis	3.54	3.99	4.73	3.94	4.43	4.98	4.54	6.19	7.56	6.19	6.48
Consumptionbeta	-0.01	0.00	0.02	0.03	0.04	0.04	0.03	0.04	0.07	0.16	0.17
	[-0.48]	[0.22]	[0.63]	[0.77]	[0.77]	[0.75]	[0.77]	[0.77]	[0.83]	[0.90]	[0.89]
Downside cons. beta	0.22	0.24	0.25	0.26	0.26	0.27	0.27	0.26	0.28	0.34	0.34
	[3.93]	[3.57]	[2.91]	[2.29]	[2.13]	[1.99]	[1.99]	[2.20]	[1.50]	[0.94]	[0.92]
Marketbeta	0.11	0.12	0.13	0.14	0.14	0.14	0.14	0.14	0.16	0.22	0.22
	[4.41]	[4.97]	[5.93]	[5.88]	[6.01]	[5.37]	[6.01]	[5.63]	[5.97]	[4.97]	[4.75]
Downsidebeta	-0.01	0.04	0.05	0.09	0.10	0.10	0.10	0.10	0.19	0.37	0.40
	[-0.49]	[1.23]	[1.70]	[2.81]	[3.02]	[2.92]	[3.05]	[3.06]	[5.17]	[6.56]	[6.94]
Upsidebeta	0.24	0.24	0.22	0.20	0.20	0.20	0.20	0.20	0.16	0.07	0.06
	[6.42]	[6.90]	[6.00]	[5.50]	[5.96]	[5.92]	[5.88]	[6.19]	[3.86]	[1.06]	[0.77]
Coskewness	0.67	0.48	0.26	0.08	0.00	-0.02	-0.01	-0.05	-0.70	-2.06	-2.41
	[4.40]	[2.91]	[1.27]	[0.44]	[-0.02]	[-0.12]	[-0.08]	[-0.26]	[-3.26]	[-6.44]	[-7.41]

Table 3.2. GMM estimates of risk premiums

The table reports GMM estimates of monthly consumption and market risk premiums (in percent per month) obtained for the 10 currency portfolios, sorted by the forward discount, and the 10-1 HML portfolio using the identity and the efficient weighting matrices. The global market index serves as a proxy for the market portfolio. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for all moments are reported. P-value for J statistics is in parentheses. Jan 1984 – June 2013.

	C-CAPM		Downside C-CAPM		CAPM		Downsidebeta CAPM		Upsidebeta CAPM		Coskewness CAPM	
Weightingmatrix	Iden.	Effic.	Iden.	Effic.	Iden.	Effic.	Iden.	Effic.	Iden.	Effic.	Iden.	Effic.
Premium	6.24	8.56	3.90	12.77	16.67	13.42	3.27	3.96	-4.84	-9.22	-0.48	-0.56
	[0.58]	[0.87]	[0.40]	[0.31]	[1.02]	[2.34]	[3.29]	[6.29]	[-2.53]	[-2.29]	[-4.18]	[-7.38]
Constant	0.32	0.06	-1.20	-2.91	-3.05	-1.45	-0.13	-0.04	1.64	2.12	0.27	0.20
	[0.26]	[0.42]	[-0.32]	[-0.31]	[-0.92]	[-1.91]	[-0.42]	[-0.95]	[2.99]	[2.38]	[0.65]	[3.35]
J-stat	5.86	5.23	10.06	9.43	18.05	12.25	4.85	3.14	15.79	14.31	7.03	6.45
	(0.75)	(0.81)	(0.35)	(0.40)	(0.03)	(0.20)	(0.85)	(0.96)	(0.07)	(0.11)	(0.63)	(0.69)
MSSE	0.18	0.18	0.13	0.13	0.17	0.17	0.12	0.12	0.12	0.12	0.17	0.18

Table 3.3. Downside risk premiums for currency and stock portfolios

The table reports the efficient GMM estimates of the global market beta, downside beta and coskewness premiums (in percent per month), estimated jointly for 5 currency portfolios, sorted by the forward discount, and 5 stock portfolios, sorted by their 5-year downside betas. Two sets of currency portfolios are considered: all countries and developed countries only. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for stock and currency moments are reported. P-value for J statistics is in parentheses.

	Downside beta CAPM		Coskewness CAPM		CAPM	
	All countries	Dev. countries	All countries	Dev. countries	All countries	Dev. countries
Premium	1.69	0.93	-0.36	-0.19	3.69	1.39
	[7.33]	[4.29]	[-4.55]	[-3.26]	[5.24]	[3.46]
Constant	-0.39	0.00	0.16	0.27	-0.60	-0.12
	[-3.25]	[0.02]	[1.47]	[2.06]	[-3.30]	[-0.82]
J-stat	5.75	4.50	3.93	2.13	14.15	5.69
	(0.76)	(0.88)	(0.92)	(0.99)	(0.12)	(0.77)
MSSE (currencies)	0.07	0.08	0.05	0.08	0.07	0.10
MSSE (stocks)	0.17	0.16	0.16	0.16	0.24	0.22

Table 3.4. Different thresholds for the downside betas and disaster betas

The table reports the efficient GMM estimates of the global 'extreme' downside betas and 'disaster betas' of 10 currency portfolios, sorted by the forward discounts (panel A), and the efficient GMM estimates of the downside beta premiums (in percent per month) using different cut-off levels for the downside betas (panel B). The downside betas are estimated using the following dummy variables: Dummy 1 = 1 if $r_m>\mu$ and 0 otherwise, Dummy 2 = 1 if $r_m>\mu-0.5\sigma$ and 0 otherwise, Dummy 3 = 1 if $r_m>\mu-\sigma$ and 0 otherwise, Dummy 4 = 1 if $r_m>\mu-1.5\sigma$ and 0 otherwise, where μ is the mean global market return and σ is the return standard deviation; Disaster dummy = 0 in the month in which there was a disaster according to Ranaldo and Soderlind (2010) classification of disasters (Appendix) and 1 otherwise. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for all moments are reported. P-value for J statistics is in parentheses.

Panel A: Extreme downside betas

	Pfl 1	2	3	4	5	6	7	8	9	Pfl 10
Extreme downside beta	0.05	0.08	0.10	0.13	0.14	0.15	0.14	0.15	0.22	0.48
(dummy4)	[1.53]	[2.64]	[2.84]	[3.80]	[3.76]	[3.84]	[4.00]	[4.23]	[5.63]	[7.51]
Disasterbeta	0.16	0.16	0.21	0.23	0.23	0.24	0.23	0.25	0.32	0.48
(disaster dummy)	[4.42]	[4.09]	[5.70]	[5.73]	[5.56]	[5.23]	[5.41]	[5.79]	[8.42]	[8.15]

Panel B: Downside risk premiums in the CAPM with

	Dummy 1	Dummy 2	Dummy 3	Dummy 4	Disasterdummy
Premium	3.95	4.26	4.60	4.69	4.86
	[6.56]	[6.11]	[6.40]	[7.19]	[4.94]
Constant	-0.03	-0.02	-0.13	-0.30	-0.80
	[-0.20]	[-0.14]	[-0.98]	[-2.26]	[-2.85]
J-stat	2.87	2.17	6.07	5.48	4.50
	(0.97)	(0.99)	(0.73)	(0.79)	(0.88)
MSSE	0.12	0.12	0.12	0.12	0.06
Number of 'extreme' observations	164	99	45	26	41

Table 3.5. Return and risk characteristics of 5 currency portfolios of developed countries and the risk premiums

The table reports the annualized returns, the return standard deviation and skewness, the efficient GMM estimates of the consumption betas, global market betas, disaster betas and coskewness of 5 currency portfolios of developed countries, sorted by the forward discounts (panel A), and the efficient GMM estimates of consumption and market risk premiums (panel B). T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for all moments are reported. P-value for J statistics is in parentheses. Jan 1984 - June 2013.

Panel A: Return and risk characteristics

	Pfl 1	2	3	4	Pfl 5
Annualized excess return (%)	-0.05	1.31	3.48	3.17	5.54
Standarddeviation (%)	34.95	34.63	33.89	34.27	37.26
Skewness	0.33	0.04	-0.02	-0.42	-0.23
Consumptionbeta	-0.02	0.01	0.05	0.05	0.10
	[-0.10]	[0.07]	[0.22]	[0.24]	[0.43]
Downside cons. beta	0.36	0.41	0.47	0.46	0.52
	[1.04]	[1.33]	[1.46]	[1.46]	[1.41]
Marketbeta	0.13	0.20	0.22	0.26	0.31
	[3.15]	[4.55]	[4.58]	[5.81]	[6.22]
Downside market beta	-0.04	0.06	0.11	0.15	0.23
	[-0.51]	[0.81]	[1.39]	[2.03]	[3.25]
Extremedownsidebeta	-0.01	0.10	0.15	0.17	0.28
	[-0.22]	[1.36]	[1.91]	[2.38]	[3.63]
Disasterbeta	0.02	0.15	0.28	0.28	0.42
	[0.22]	[2.34]	[3.80]	[3.95]	[6.83]
Upside market beta	0.31	0.33	0.35	0.36	0.39
	[5.51]	[6.33]	[6.78]	[7.14]	[6.22]
Coskewness	1.25	0.77	0.31	0.41	-0.18
	[3.47]	[1.89]	[0.70]	[0.94]	[-0.43]

Panel B: Riskpremiums

	C-CAPM	Downside C-CAPM	CAPM	Downside beta CAPM	Extremedownsidebeta CAPM	Disasterbeta CAPM	Upsidebeta CAPM	Coskewness CAPM
Premium	3.90	3.25	2.66	1.80	1.75	1.26	8.05	-0.36
	[0.60]	[0.43]	[2.37]	[2.47]	[2.61]	[3.28]	[1.11]	[-2.31]
Constant	0.05	-1.20	-0.35	0.07	0.03	-0.03	-2.55	0.44
	[0.05]	[-0.34]	[-1.27]	[0.38]	[0.14]	[-0.16]	[-1.00]	[1.89]
J-stat	4.53	1.39	3.45	1.62	1.16	0.63	3.93	0.37
	(0.34)	(0.85)	(0.48)	(0.81)	(0.88)	(0.96)	(0.42)	(0.98)
MSSE	0.20	0.15	0.19	0.14	0.14	0.11	0.14	0.20

Table 3.6. Downside risk in the period of active carry trades (2000-2013)

The table reports the annualized returns and the efficient GMM estimates of the global market betas and coskewness of 10 currency portfolios (all currencies - AC) and 5 currency portfolios (developed countries - DC), all sorted by the forward discounts, in panel A, and the efficient GMM estimates of various market risk premiums (in percent per month) in panel B. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for all moments are reported. P-value for J statistics is in parentheses. Jan 2000 – June 2013.

Panel A: Return and risk characteristics

All currencies (AC)

	Pfl 1	2	3	4	5	6	7	8	9	Pfl 10
Annualized excess return (%)	0.71	0.82	1.99	5.00	4.05	6.57	1.81	5.84	8.33	12.71
Marketbeta	0.16	0.21	0.24	0.30	0.28	0.32	0.24	0.31	0.36	0.41
	[5.38]	[8.57]	[9.19]	[10.91]	[11.27]	[11.10]	[8.69]	[9.41]	[13.74]	[12.00]
Downsidebeta	0.09	0.14	0.16	0.23	0.23	0.26	0.19	0.27	0.34	0.47
	[2.79]	[5.75]	[4.62]	[5.91]	[6.40]	[6.77]	[4.87]	[6.48]	[6.96]	[7.80]
Extremedownsidebeta	0.15	0.19	0.22	0.27	0.27	0.31	0.22	0.33	0.38	0.52
	[5.22]	[8.76]	[6.98]	[8.62]	[8.15]	[9.17]	[7.02]	[8.89]	[9.47]	[8.81]
Disasterbeta	0.16	0.18	0.23	0.26	0.27	0.32	0.24	0.32	0.40	0.52
	[4.61]	[5.58]	[6.40]	[6.14]	[6.57]	[8.09]	[5.41]	[7.26]	[13.00]	[9.54]
Coskewness	-0.24	-0.38	-0.63	-0.92	-0.93	-1.12	-0.64	-1.29	-1.64	-2.48
	[-1.36]	[-1.99]	[-2.89]	[-3.59]	[-3.66]	[-3.69]	[-2.54]	[-4.01]	[-4.99]	[-5.37]

Currencies of developed countries (DC)

	Pfl 1	2	3	4	Pfl 5
Annualized excess return (%)	1.09	1.10	3.10	2.87	6.95
Marketbeta	0.18	0.28	0.30	0.34	0.36
	[3.46]	[6.00]	[5.49]	[7.05]	[8.00]
Downsidebeta	0.14	0.19	0.25	0.29	0.38
	[2.42]	[3.59]	[3.71]	[5.21]	[5.00]
Extremedownsidebeta	0.17	0.24	0.29	0.32	0.46
	[3.14]	[4.91]	[4.59]	[6.12]	[6.24]
Disasterbeta	0.13	0.21	0.32	0.31	0.51
	[1.69]	[4.05]	[4.62]	[4.65]	[8.24]
Coskewness	-0.40	-0.48	-0.86	-0.90	-1.37
	[-1.41]	[-1.50]	[-2.63]	[-2.83]	[-2.90]

Panel B: Riskpremiums

	CAPM		Downsidebeta CAPM		Extremedownsidebeta CAPM		Disasterbeta CAPM		Coskewness CAPM	
	AC	DC	AC	DC	AC	DC	AC	DC	AC	DC
Premium	3.50	3.23	3.32	2.32	3.60	2.26	3.15	1.74	-0.54	-0.56
	[4.81]	[2.31]	[4.76]	[2.81]	[4.57]	[3.02]	[4.35]	[3.19]	[-4.07]	[-2.05]
Constant	-0.48	-0.37	-0.26	-0.30	-0.58	-0.31	-0.51	-0.17	-0.14	-0.18
	[-3.11]	[-1.37]	[-3.17]	[-1.34]	[-3.38]	[-1.45]	[-2.46]	[-0.68]	[-2.53]	[-0.74]
J-stat	6.59	3.97	3.99	3.96	4.36	1.95	3.34	1.17	4.70	1.99
	(0.68)	(0.91)	(0.91)	(0.91)	(0.89)	(0.99)	(0.95)	(1.00)	(0.86)	(0.99)

MSSE	0.07	0.08	0.05	0.06	0.05	0.06	0.05	0.06	0.08	0.09

Table 3.7. Comparison of alternative risk factors for currency portfolios

The table reports the efficient GMM estimates of risk premiums of different risk factors, estimated for the currency portfolios, sorted by the forward discounts. Alternative 1-factor and multifactor models are considered. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) are reported. P-value for J statistics is in parentheses.

	1	2	3	4	5	6	7	8	9	10	11
Downside market factor	0.04				0.04	0.04	0.03			0.02	-0.07
	[4.66]				[3.67]	[2.47]	[1.44]			[1.87]	[-0.19]
Market volatility factor		-0.006			-0.005			-0.005	-0.006	-0.008	0.024
		[-5.09]			[-2.82]			[-3.00]	[-0.73]	[-1.96]	[0.23]
Currency volatility factor			-0.22			-0.06		-0.04		-0.03	
			[-3.14]			[-1.04]		[-0.57]		[-0.32]	
HML factor				0.01			0.01		0.01		0.01
				[7.35]			[6.94]		[5.61]		[5.99]
Intercept	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01
	[-0.22]	[2.06]	[0.91]	[1.82]	[-0.02]	[-0.64]	[-0.46]	[2.09]	[-0.07]	[1.17]	[-0.23]
J-stat	0.82	1.75	2.38	2.26	1.00	1.16	1.49	1.10	0.65	0.86	0.01
	(0.94)	(0.78)	(0.67)	(0.69)	(0.91)	(0.88)	(0.83)	(0.89)	(0.96)	(0.93)	(1.00)
MSSE	0.09	0.14	0.11	0.13	0.09	0.09	0.09	0.09	0.06	0.06	0.07

Table 3.8. Comparison of alternative risk factors for stock portfolios

The table reports the efficient GMM estimates of risk premiums, estimated for the 5 stock portfolios, sorted by their 5-year downside betas. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) are reported. P-value for J statistics is in parentheses.

	Downside market factor	Market volatility factor	Currency volatility factor	HML factor
Premium	0.01	-0.001	-0.03	0.016
	[2.29]	[-1.99]	[-1.78]	[1.35]
Intercept	0.00	0.00	0.00	0.00
	[1.79]	[2.28]	[2.22]	[0.86]
J-stat	1.16	0.81	0.59	1.76
	(0.76)	(0.85)	(0.90)	(0.62)
MSSE	0.23	0.29	0.31	0.30

Table 3.9. Currency portfolios sorted by the downside betas

The table reports the annualized returns and the efficient GMM estimates of the global downside market betas and coskewness of 5 currency portfolios, sorted by the downside betas, estimated in a 5-year rolling window prior to the sort date, in panel A, and the efficient GMM estimates of market risk premiums (in percent per month) in panel B. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) for all moments are reported. P-value for J statistics is in parentheses.

Panel A: Return and risk characteristics					
	Pfl 1	2	3	4	Pfl 5
Annualized excess return (%)	3.34	3.50	3.87	3.61	8.52
Beta	0.13	0.15	0.23	0.23	0.26
	[4.57]	[4.43]	[5.36]	[4.77]	[5.26]
Downside beta	0.15	0.19	0.22	0.24	0.41
	[2.95]	[4.36]	[5.24]	[4.99]	[8.53]
Extreme downside beta	0.20	0.24	0.27	0.28	0.44
	[3.42]	[4.87]	[6.06]	[6.44]	[7.76]
Disaster beta	0.21	0.24	0.26	0.29	0.43
	[3.52]	[4.95]	[5.58]	[5.82]	[9.01]
Coskewness	-0.62	-0.79	-0.73	-0.84	-1.66
	[-2.86]	[-3.99]	[-2.86]	[-3.15]	[-4.12]

Panel B: Risk premiums					
	CAPM	Downside beta CAPM	Extreme down beta CAPM	Disaster beta CAPM	Coskewness CAPM
Premium	1.14	2.11	2.28	2.33	-0.46
	[1.18]	[2.45]	[2.23]	[2.10]	[-2.28]
Constant	0.15	0.02	-0.09	-0.15	0.02
	[0.82]	[0.07]	[-0.31]	[-0.43]	[0.10]
J-stat	1.43	1.47	1.87	2.00	0.86
	(0.84)	(0.83)	(0.76)	(0.74)	(0.93)
MSSE	0.11	0.04	0.04	0.04	0.07

Table 3.10. Risk premiums in the long run: 1974-2013

The table reports the efficient GMM estimates of consumption and market risk premiums, estimated for 10 currency portfolios of developed and emerging countries, sorted by the nominal interest rate differential. T-statistics are in brackets, t-statistics are calculated using heteroskedasticity consistent standard errors. J statistics for the overidentifying restrictions and the mean sum of squared errors (MSSE) are reported. P-value for J statistics is in parentheses. Jan 1974 - June 2013.

	C-CAPM	CAPM	Downside beta CAPM	Upside beta CAPM	Extreme downside beta CAPM	Coskewness CAPM
Premium	4.96	27.47	4.09	-7.55	3.75	-0.53
	[1.31]	[1.17]	[4.50]	[-2.46]	[5.13]	[-5.81]
Constant	-0.03	-3.53	-0.12	1.58	-0.29	0.12
	[-0.56]	[-1.08]	[-1.57]	[2.55]	[-2.19]	[3.14]
J-stat	3.33	15.86	6.27	16.72	5.90	8.50
	(0.95)	(0.07)	(0.71)	(0.05)	(0.75)	(0.48)
MSSE	0.24	0.23	0.17	0.17	0.16	0.24

Chapter 4

Currency Exposure to Downside Risk: Which Fundamentals Matter?

4.1. INTRODUCTION

If currencies serve as investment assets, the correlation of exchange rates with the stock market (or the market beta) is importantfor a diversifying investor. Currency exposure to downside risk, i.e. a conditional correlation of exchange rates with the market in times of low market returns (or the downside beta), is particularly important because the marginal utility of wealth is high in such ‘hard times’.

A growing volume of empirical evidence suggests that currency returns are not random; some currencies tend to move together with the stock market and depreciate in periods of low market returns and high volatility, while others seem to be immune to stock market downturns and, thus, can serve as a hedging instrument. In this chapter, I study whether or not there is a systematic relationship between currency exposure to the downside market risk and macroeconomic characteristicsof the respective countries. I try to answer the question as to which currencies tend to crash when the stock market goes down and which currencies serve as a ‘safe haven’.

The main findings of the paper can be summarized as follows. Firstly, currencies systematically differ in terms of their exposure to the downside risk indeed and the spread in the downside betas of currencies is high and significant. Moreover, currency exposure to the downside risk has increased dramatically since the beginning of the 21st century in parallel with the growing volume of currency trading.

Secondly, currency downside betas are strongly associated with particular levels of three out of eight macroeconomic variables considered: the inflation rate, the real interest rate and the net foreign asset position. Countries with high inflation rates, high real interest rates and low (negative) net foreign assets have currencies with high exposure to the downside risk whereas countries with the opposite characteristics have currencies with ‘safe haven’ properties.

These three macroeconomic variables are, in fact, related, because higher inflation and higher real interest rates in an economy lead to higher nominal interest rates and higher nominal currency returns, which, in turn, lead to higher capital inflows and lower net foreign assets. The high explanatory power of these variables for the downside risk suggests that the direction of currency trading is the reason why some currencies are exposed to the downside risk more than others. Currencies of debtor countries with high returns (investment currencies) have higher exposure to the downside risk because capital is withdrawn in bad times. Currencies of creditor countries with low returns (funding currencies) provide a hedge in bad times because capital flies back to them.

In a multivariate setting, when inflation and/or real interest rates are controlled for, the net foreign asset position becomes an insignificant determinant of currency downside risk. Whereas the real interest rate has the highest explanatory power in the recent ‘post-euro’ period, the inflation rate was a better determinant of currency risk in the 90s. I do not find evidence, that other macroeconomic variables, previously suggested in the literature, are systematically related to currency risk.

The relationship between exchange rates and stock market returns has already been explored in Campbell et al. (2010) and Ranaldo and Söderlind (2009) for the currencies of fewdeveloped countries. Campbell et al. (2010) find a consistent positive correlation of the Australian dollar and the Canadian dollar with the global equity markets and a negative correlation of the euro and the Swiss franc. The Japanese yen, the British pound and the US dollar fall in the middle of the two extremes. A high-frequency analysis in Ranaldo and Söderlind (2009) uncovers a similar pattern; the Swiss franc and the Japanese yen (and to a lesser extent the euro) appreciate when the US stock market goes down, while the opposite is observed for the British pound. The 'safe haven' properties of the Swiss franc and the Japanese yen are confirmed in periods of political, natural or financial disasters.

The abovementioned studies look at the overall market risk of currencies, whereas my paper is devoted to the analysis of currency downside risk. The downside beta is, perhaps, a better measure of risk than the traditional beta because it reflects an asset's performance in the worst states of the world when the overall market return is low and the marginal utility of wealth is high. The choice of the downside beta as a measure of risk was motivated by Ang et al. (2006), who consider investors with disappointment aversion utility function, derive a two-beta CAPM with an upside beta and a downside beta and show that the downside betas explain the cross-section of stock returns better than the traditional betas whereas the upside betas are completely irrelevant. Two recent studies of the downside risk (Lettau et al., 2014, and Dobrynskaya, 2014) confirm that assets' exposure to the downside risk has a much greater explanatory power for returns in currency, stock, bond and commodities markets than assets' overall market risk.

In a closely related recent study by Habib and Stracca (2012), the authors look at the macroeconomic determinants of currencies' 'safe haven' properties, measured by their exposure to stock market volatility VIX. They find that, out of 20 macroeconomic fundamentals considered, the nominal interest rate differential, public debt to GDP ratio, the net foreign asset position, financial development and liquidity are associated with 'safe haven' behavior of currencies of advanced economies, while only the net foreign asset position and the size of the stock market are relevant for emerging economies. They conclude that "the net foreign asset position is the most consistent fundamental determinant of the safe haven status…" A similar conclusion about the validity of net foreign assets in explaining currency 'safe haven' behavior is drawn in Cenedese (2012) using a portfolio approach.

My paper contributes to the above studies in several ways. Firstly, rather than studying only the determinants of 'safe haven' currencies, I study the determinants of currencies with both low and high exposure to the downside risk. Secondly, we employ different methodologies and use different measures of currency downside risk. I measure the exposure to the downside risk as the downside market beta, whereas Habib and Stracca (2012) define 'safe haven' currencies as those that appreciate in times of high market volatility. Thirdly and most importantly, I provide an explanation why net foreign asset position is a relevant determinant of currency downside risk, I show that the real interest rate has an even higher explanatory power, especially in the 'post euro' period, and once the real interest rate is controlled for, the net foreign asset position becomes statistically insignificant.

Rather than looking at few particular currencies, I take a sample of 47 major currencies of developed and developing countries. The big sample of currencies allows me to run cross-sectional tests for individual currencies as well as to build currency portfolios sorted by macroeconomic characteristics. The portfolio approach has an advantage that the measurement errors of betas are minimized and it allows to account for time variation in betas. I also look at a longer period of time, compared to the abovementioned studies, and analyze trends over time. My results are robust to different sub-samples of currencies, different sub-periods and different methods employed.

My findings also shed some light on why a carry trade is a very risky investment strategy. A carry trade – borrowing in low nominal interest rate currencies and investing in high nominal interest rate currencies – generates high excess returns which are negatively skewed (Brunnermeier et al., 2008) and have high stock market beta (Lustig and Verdelhan, 2010) and an even higher downside market beta (Dobrynskaya, 2014). Since nominal interest rates can be high due to high real interest rates, high inflation rates or both, I decompose nominal interest rates into inflation and real interest rates and form double-sorted currency portfolios. I show that currencies with the same level of real interest rates but different inflation rates have the same downside risk, whereas, controlling for inflation, currencies with higher real interest rates have a higher downside risk. Therefore, the high downside risk of carry trades turns out to be a consequence of high real interest rates in the investment countries and low real interest rates in the funding countries, rather than the nominal interest rates. When nominal and real interest rates correlate significantly (e.g. in developed countries), high levels of these rates in an economy are both associated with the high downside risk of its currency, but when the correlation between these rates is low, only the real interest rate is associated with currency downside risk.

The rest of the chapter is organized as follows. I describe the datain section 4.2. Section 4.3 is devoted to results. In section 4.3.1, I analyze currency portfolios sorted by their downside betas, I show that there are indeed significant differences in the downside risk exposure of currencies, and I provide average macroeconomic characteristics of these portfolios. Section 4.3.2 is devoted to a cross-sectional regression analysis of downside risk for individual currencies whereasin section 4.3.3I show the risk characteristics of currency portfolios sorted by various macroeconomic variables. Section 4.4 concludes the paper.

4.2.DATA

The data covers the period from January 1990 until December 2012. Earlier years are not considered because of the predominance of fixed exchange rate regimes around the world and limited macroeconomic data for many countries. Because the introduction of euro changed the composition of countries significantly, I perform the analysis for two sub-periods: ‘pre-euro’ period 1990-1998 and ‘post-euro’ period 1999-2012.

The total sample of countries consists of 47major developed and emerging economies with the highest volume of currency turnover and available macroeconomic data. Countries with fixed exchange rate regimes are not considered because their artificially low exchange rate risk would bias the analysis.The effective samples of countries are different (but overlapping) in the two sub-periods because the post-soviet countries are excluded in the 'pre-euro' period and the euro zone countries are excluded in the 'post-euro' period. Because of these restrictions, there are 36 currencies in each sub-period.The samples of currencies in the two sub-periods are reported in appendix A2.

Exchange rate returns and total returns (including the interest rate differentials, or forward discounts) are measured on a monthly frequency. An increase in the exchange rate means an appreciation of the respective currency against the US dollar. The MSCI AC World index is used as a proxy for the market portfolio to estimate the downside market risk.

Since many macroeconomic variables are only available on an annual frequency, I use annual time series of all macroeconomic data. The following macroeconomic variables are considered: the CPI inflation rate (from World Economic Outlook), the real lending interest rate (from World Bank), net foreign assets (NFA) relative to local GDP (from Milesi-Feretti database[33]), the current account relative to local GDP (from World Economic Outlook), the GDP share of the world GDP based on purchasing power parity (from World Economic Outlook), the market capitalization of listed companies relative to local GDP (from World Bank), the market volume of stock trades relative to local GDP (from World Bank), the Fitch country rating, converted to numeric scale from 1 to 24, where a higher number means a higher country risk. All macroeconomic data is available for the whole period of study except the Fitch country rating, which covered only a few countries in the early 90s. Therefore, I only use it in the second sub-period 1999-2012.

The choice of the macroeconomic variables is motivated by previous studies (Habib and Stracca, 2012; Hassan, 2013; Cenedese, 2012) which show that some of these variables have explanatory power for currency returns and risk.

[33] I thank Gian Maria Milesi-Ferretti for kindly sharing their data on countries' external positions.

4.3.RESULTS

4.3.1. CURRENCY PORTFOLIOS SORTED BY THE DOWNSIDE BETAS

First of all, I show that the downside market risk of currenciesis important indeed and varies significantly across currencies and over time. The downside market risk is measured by the downside beta which is defined as a market beta conditional on a negative performance of the stock market; it shows how a currency'sreturn changes when the global stock market goes down. I estimate the downside betas on monthly returns for each sub-period separately in the following regression:

$$\Delta er_{jt} = \alpha_j + \beta_j r_{mt} + \delta_j dummy_t * r_{mt} + \varepsilon_{jt} \qquad (4.1)$$

where Δer_{jt} is the exchange rate return of asset j, r_{mt} is the stock market return, $dummy_t = \begin{cases} 0, r_{mt} < 0 \\ 1, r_{mt} > 0 \end{cases}$ and β_j is the estimate of downside beta[34]. A positive value of β_j means that the currency systematically depreciates when the stock market return is negative, and a higher value of β_j reflects a higher currency exposure to the downside risk. A close-to-zero downside beta reflects 'safe haven' properties of a currency.

The individual currency downside betas are often highly statistically significant and the range of downside betas across currencies is wide. In the first sub-period 1990-1998, the lowest downside beta of -0.19 is observed for Japanese yen, and the highest downside beta of 0.39 is observed for Polish zloty. In the second sub-period 1999-2009, the downside risk of all currencies is generally much higher. The Japanese yen has the lowest downside beta of -0.09 again, whereas the highest downside beta of 0.71 is observed for Turkish lira. Other countries with the highest downside risk of their currencies are Brazil, Australia, New Zealand and

[34] It is also possible to estimate the downside betas by putting the total currency returns (including the interest rate differential) on the left-hand side of equation (4.1). The downside betas estimated in this way do not differ from the exchange rate downside betas by more than 0.02, which suggests that all market risk of currencies comes from exchange rate fluctuations. Since the data on interest rates is not available for all currencies in the earlier years, I consider the exchange rate downside betas throughout the paper.

South Africa. The full list of currencies and their downside betas in the two sub-periods is presented in appendix A2.

Since individual currency betas can be measured with errors, to get a more reliable picture of the downside risk of currencies, I sort 36 currencies in each sub-period by their individual downside betas into 6 equal-weighted portfolios and estimate the downside betas and average macroeconomic characteristics for these portfolios[35]. Portfolios with higher ranks contain currencies with higher downside betas. Table 4.1 reports the results.

The portfolio downside betas range from -0.12 to 0.23 in the first sub-period and from 0.05 to 0.57 in the second sub-period. Currencies in the top portfolios systematically depreciate when the stock market performs poorly, whereas currencies in portfolio 1 are generally immune to the stock market downturns and can serve as a hedging instrument.The differences between the downside betas of the top and the bottom portfolios are statistically significant in the both sub-periods, although the individual portfolio downside betas are only significant in the second sub-period.

The beginning of the 21st centuryis marked by a much greater stock market risk of currencies. The downside betas are more than twice as high as they were in the 90s, the increase is more than 2 standard deviations and is statistically significant. This is a sign of a greater interdependence of the currency and the stock markets, but it can also be a result of more flexible exchange rate regimes and lower foreign exchange interventions in many countries. Furthermore, it can be a result of a higher carry trade activity, as evidenced in Galati et al. (2007), and unwinding of carry trade positions.

Currency portfolios with higher downside risk have higher average returns in the both sub-periods in line with the findings of Dobrynskaya (2014) and Lettau et al. (2014) that the downside risk explains the cross-section of currency returns well.

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[35]Sorting by the traditional market betas produces a similar picture, although sorting by the downside betas gives the biggest rangein the market risk across portfolios.

Table 4.1 also reports the average macroeconomic characteristics of the 6 currency portfolios. Countries with higher currency exposure to the downside risk tend to have higher inflation and real interest rates (and, hence, higher nominal interest rates), lower (negative) net foreign asset positions and current accounts (debtor countries), somewhat lower size, market capitalization and market volume, and somewhat higher country risk. Countries with the lowest downside risk have the opposite characteristics. But none of the 8 macroeconomic variables considered exhibit strict monotonicity across portfolios, because there are often exclusions to the general trend. The highest explanatory power in terms of the cross-sectional R^2 is observed for the inflation and real interest rates, lower explanatory power for the external position (net foreign assets and current account), and almost no explanatory power for the country and stock market size (GDP share, market capitalization and market volume) and country risk.The next sections explore these relationships thoroughly.

4.3.2. CROSS-SECTIONAL ANALYSIS OF INDIVIDUAL CURRENCIES

This section is devoted to a cross-sectional analysis of the determinants of the downside risk of individual currencies. I estimate alternative univariate and multivariate specifications with the downside betas on the left-hand side and country average macroeconomic characteristics on the right-hand side[36]. The analysis is performed for the two sub-periods separately, and there are 36 cross-sectional observations in each sub-period. The estimation results are reported in table 4.2.

Among the univariate specifications (1)-(8), only inflation rate, real interest rate and net foreign assets have statistically significant coefficients in the both sub-periods[37]. As before,

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[36] Although the downside betas of individual currencies may be estimated with errors, this does not affect the regression coefficients because the betas are the dependent variables in these specifications and, hence, the common measurement error problem in asset pricing is irrelevant here.

[37] In alternative specifications with the *traditional* market betas on the left-hand side, none of the variables was statistically significant in the first sub-period. Hence, it was very difficult to explain the overall market risk of currencies which was rather random in that period.This is, perhaps, the reason why many early studies of exchange rate dynamics concluded that currency returns are random and are not related to macroeconomic variables.

countries with higher inflation and real interest rates and lower net foreign assets have higher exposure to downside risk. Regressions with these variables also have the highest cross-sectional R^2. Out of these three variables, the inflation rate and net foreign assets had the highest explanatory power in the first sub-period, whereas the real interest rate has the highest explanatory power in the second sub-period. All other macroeconomic variables are insignificant determinants of the currency downside risk, although the coefficients have the correct signs in accordance with the findings of Hassan (2013) and Habib and Stracca (2012).

In bivariate specifications (9) and (10), I include two of the abovementioned significant variables[38] and find that all of them are still significant in 1990-1998 and only the real interest rate remains significant in 1999-2012. When other macroeconomic characteristic are controlled for (specifications (11) and (12)), the net foreign asset position loses its explanatory power, whereas the inflation and real interest rates remain the only significant determinants of currency downside risk in the both sub-periods. In 1990-1998, the inflation and real interest rates were almostperfectly correlated, and it is impossible to determine which one is a better determinant of currency risk. But in 1999-2012, these variables were almost uncorrelated, and when they are included together (specification (12)), the real interest rate survives as the only statistically significant regressor.The inflation rate does not play a role in the more recent period because most countries managed to stabilize it.

It should be noted that not only the downside risk is higher in the second sub-period, but also the explanatory power of the macroeconomic variables is higher. The 8 macroeconomic fundamentals considered can jointly explain up to 40 percent of cross-sectional variation in currency downside risk, whereas the real interest rate alone can explain about 20 percent of it.

Since inflation and real interest rates determine nominal interest rates and nominal currency returns which, in turn, determine capital flows and net foreign asset position, these variables are related. Their high explanatory power for the cross-section of currency exposure

[38] The inflation rate and the real interest rate cannot be included together in 1990-1998 because of their high correlation of 0.97.

to the downside risk suggest that the *direction* of currency trading is the primary determinant of currency risk.

Countries with high inflation (in the earlier years) and high real interest rates (in the more recent years) provide higher nominal returns to investors[39] and, hence, have negative net foreign asset positions and negative current accounts (i.e. capital inflows). But in bad times, when the global stock market plunges, capital is withdrawn from these countries and these currencies depreciate. Therefore, these currencies are more vulnerable in severe stock market conditions.

Countries with low inflation and real interest rate, on the contrary, provide low currency returns and become donor countries with positive net foreign asset positions and positive current accounts (i.e. capital outflows). In bad times, capital does not flow from these countries, and these currencies do not depreciate. Moreover, they may even appreciate if capital is returned. Such currencies are 'safe haven' currencies because they provide a hedge against the global downside risk.

My results also suggest that the high downside market risk of carry trades, which is clamed to explain the high returnsto this strategy (Lettau et al, 2014; Dobrynskaya, 2014),is a consequence of the big difference in the *real* interest rates of investment and funding currencies, which, in turn, affect the *nominal* interest rates and currency returns.

4.3.3. CURRENCY PORTFOLIOS SORTED BY MACROECONOMIC VARIABLES

4.3.3.a. ALTERNATIVE SOTRS BY ONE MACRO VARIABLE

The previous analysis does not take into account the time variation in currency betas and macroeconomic characteristics of countries. In reality, though, a country's macroeconomic fundamentals may change over time and its currency downside risk may change accordingly. In this section, I allow for time variation in the downside risk by sorting 36 currencies in the

[39] Exchange rate fluctuations do not offset these nominal returns (e.g. Dobrynskaya, 2014) and, therefore, carry trades are so profitable.

sample into 6 portfolios based on their macroeconomic characteristics and estimating downside betas for the currency portfolios rather than for individual currencies. The portfolios are rebalanced annually. If a country's macroeconomic conditions change its currency moves to another portfolio with the respective level of the macroeconomic variable. At any point of time, a portfolio may have different currencies, but similar macroeconomic characteristics. Portfolio 1 always contains 6 currencies with the lowest value of the sort variable whereas portfolio 6 always contains currencies with the highest value of the sort variable. Some currencies do not change portfolios whereas other currencies change portfolios quite often.

This portfolio approachnot only allows me to take into account the time variation in the macroeconomic variables and currency market risk, but also allows studying the whole period 1990-2012 and derive more general results. Moreover, the downside betas are estimated for the currency portfolios instead of single currencies and, hence, the measurement errors are reduced.

If a macroeconomic variable is indeed systematically related to the currency downside risk, sorting by this variable would produce the highest spread inthe downside betas of the top and bottom portfolios because, for instance, portfolio 6 would always pick the currencies with the highest value of the macro variable in the respective period and, hence, the highest downside risk. Since macroeconomic variables and the currency risk vary over time, periodic rebalancing should result in the most striking differences between the betas of the portfolios. We should also find a monotonic relationship between the downside betas and portfolio rank if the sort variable is a relevant one.

The whole period 1990-2012

Panel A of table 4.3reportsthe downside betas of seven groups of portfolios, sorted by the seven macroeconomic variables considered. The last column shows the characteristics of the high-minus-low (HML) portfolio which takes a long position in portfolio 6 and a short position in portfolio 1. The downside betas of these long-short portfolios are equal to the differences in the downside betas of portfolios 6 and 1, and their statistical significance means that the differences in the betas of the top and the bottom portfolios are statistically significant.

The average values of the sort variables for each portfolio are presented in the first line of each panel. They are increasing with the portfolio rank because this is how the portfolios were sorted.

We observe strict monotonicity of the downside betas in the cases when portfolios were sorted by inflation rates, real interest rates and net foreign asset positions. Portfolios with higher levels of inflation and real interest rates and lower levels of net foreign assets have higher downside betas (the highest portfolio downside betais 0.35). The downside betas are always statistically significant, expect for the portfolios with the lowest level of inflation and real interest rate and the highest (positive) level of net foreign assets. These portfolios with insignificant downside betas contain ‘safe haven’ currencies.

The HML portfolios in these three alternative sorts have the highest and statistically significant downside betas, which means that portfolios with rank 6 and rank 1 have statistically different downside risk indeed. In the cases of the inflation rate sort and the real interest rate sort, portfolios with rank 6 have downside risk which is 2.5 times as high as the downside risk of portfolios with rank 1. In the case of net foreign assets sort, the downside risk of portfolio 1 is 3.5 times as high as the downside risk of portfolio 6. Sorting by net foreign assets produces the highest spread in the downside betas across the portfolios.

Although the sorting by these three macroeconomic variables produces similar results, this is not due to the same currency composition of the portfolios obtained by the alternative sorts. In fact, portfolios with the same rank are somewhat different. This is because the real interest rate and the inflation rate are rather orthogonal to each other in the recent years.

Sorting by current accounts, GDP shares, market capitalization and market volumes do not produce monotonic patterns in the downside betas. Therefore, we cannot conclude that a higher level of any of these variables is systematically associated with a higher or lower level of the downside risk. The corresponding HML portfolios also do not have statistically significant downside betas. Hence, the spread between the downside risk of the top and bottom portfolios is very low and insignificant. These macroeconomic variables seem to be irrelevant in explaining currency downside risk.

The 'post-euro' period 1999-2012

To test the robustness of the results over time, I repeat the same exercise for the second sub-period 1999-2012 separately. Panel B of table 4.3 presents the statistics of the portfolios in this recent sub-period. A striking difference is that the inflation rateof the top portfolio decreased significantly because many developing countries managed to stabilize their inflation in 90s, whereas the market capitalization and the market volume of the top portfolios increased. The currency downside risk has also increased. For any sort variable and any portfolio, the downside betas are almost twice as high as they were previously, and the spreads in the downside betas across portfolios are generally wider.

The overall results are not different in the 'post-euro' period. Only the sorts by inflation rates, real interest rates and net foreign assets produce monotonic patterns of the downside betas and significant spreads between the downside betas of the top and bottom portfolios. Other variables are irrelevant again.

Sort by the country risk also does not generate monotonically increasing pattern of the downside betas. Even though, generally, a higher country risk is associated with higher currency downside risk, portfolios 1 and 2 stand out because portfolio 1 contains Australia and New Zealand with low country risk but high currency downside risk, and portfolio 2 contains Japan with higher country risk but much lower currency downside risk.

4.3.3.b. DOUBLE SORT BY INFLATION AND REAL INTEREST RATE

Since inflation and real interest rates are related,and both affect nominal interest rates which, in turn, affect net foreign asset positions, it is important to separate the effects of inflation and real interest rates and identify which variable has higher explanatory power for the currency downside risk. For this purpose, I use the following double sorting procedure. First, all 36 currencies are sorted by inflation rate into three equal portfolios. Then, currencies of each portfolio are sorted by real interest rates and divided again into two portfolios. As previously, the portfolios are rebalanced every year. Each portfolio consists of 6 currencies, but the composition of portfolios changes over time. The descriptive statistics of the six double-sorted portfolios is presented in table 4.4.

Portfolio pairs 1 and 2, 3 and 4, 5 and 6 have similar average inflation rates but different average real interest rates both in the whole period and in the ‘post-euro’ sub-period. Therefore, the real interest rates and inflation rates are orthogonal to each other and we can separate their effects.

The downside betas of the low-real-interest-rate portfolios (1, 3 and 5) are always lower than those of the respective high-real-interest-rate portfolios (2, 4 and 6). The differences in the downside betas are always significant, except for the low-inflation portfolios in the top panel. Controlling for inflation, a higher real interest rate in an economy is associated with higher downside risk of its currency. This relationship is even stronger in the recent sub-period.

Higher inflation rate is also related to higher downside risk, but this relationship is not that strong. The differences in the downside betas of portfolios 1 and 3, 2 and 4, 3 and 5, 4 and 6 are rather small and statistically insignificant. There are some differences in the downside betas of low-inflation and medium-inflation portfolios, whereas there is almost no difference in the downside betas of medium-inflation and high-inflation portfolios despite significant differences in their inflation rates. This is particularly true in the recent sub-period.

For instance, portfolio pairs 3 and 5 and 4 and 6 have different inflation rates, similar real interest rates and similar downside betas.Therefore, controlling for the level of real interest rate, we cannot conclude that higher inflation rate is strongly associated with higher currency downside risk.

Even though lower real interest rate is associated with lower downside risk, a low level of the real interest ratealone does not ensure ‘safe haven’ properties of a currency, because countries with low real interest rates and high inflation rates have rather high downside risk (e.g. portfolio 5). ‘Safe haven’ currencies have two features: the lowest real interest rate and the lowest inflation rate at the same time. Consequently, suchcurrencies also have the lowest nominal interest rate and net foreign asset position.

Since countries with high real interest rates are supposed to have high default risk, and since their currencies also have the highest downside market risk, we can suggest that there is ‘flight to quality’ in the currency market. When the general market conditions worsen, investors sell currencies of countries with high real interest rates and accumulate currencies of safe countries with low real interest rates and low inflation rates. This results in high downside risk of the former currencies and zero (insignificant) downside risk of the latter currencies.

4.4. CONCLUSION

Several studies have shown that some particular currencies are exposed to the market risk whereas others serve as a ‘safe haven’ (Campbell et al., 2010, Ranaldo and Söderlind, 2009). In this chapter, I explore which macroeconomic characteristics are systematically related to the downside risk of currencies. I show that ‘safe haven’ currencies have low inflation and real interest rates and positive net foreign asset positions of the respective countries. Currencies which tend to crash with the stock market, on the contrary, belong to debtor countries with high real interest and inflation rates. The level of the real interest rate has the highest explanatory power in the cross-section of currency exposure to the downside risk, especially in the 2000s. This suggests that there is a 'flight to quality' in the currency market in 'hard times' (i.e. capital is withdrawn from high real interest rate risky currencies of debtor countries and returned to low real interest rate 'safe haven' currencies of creditor countries). Other macroeconomic variables, previously suggested in the literature, do not seem to play a significant role in explaining currency exposure to the downside risk.

These findings have important implications for portfolio choice when currencies are considered as investment assets. Although market betas of currencies are generally lower than market betas of stocks, currencies of countries with high real interest rates are not attractive from the point of view of portfolio diversification because of their high downside betas. In order to reduce the downside market risk of a portfolio, investing into currencies of countries with low real interest rates and low inflation rates is desirable, because such currencies tend to be stable or even appreciate when the stock market goes down and, hence, they can serve as a hedging instrument.

Table 4.1. Macroeconomic characteristics of currency portfolios sorted by downside betas

The table reports average downside betas, returns and macroeconomic characteristics of 6 currency portfolios sorted by individual currency downside betas. 36 countries are considered in each sub-period. T-statistics for the downside betas are in brackets,t-statistics are calculated using Newey-West heteroskedasticity consistent standard errors. The returns, inflation and real interest rates are reported in percent per annum. Net foreign assets, current account, market capitalization and market volume are measured in percent to local GDP. GDP share is measured relative to world GDP. Country risk is proxied by Fitch country rating on a scale from 1 to 24, a higher number means a higher risk.

	Pfl 1	2	3	4	5	Pfl 6
			1990-1998			
Downside beta	-0.12	-0.05	-0.04	0.03	0.10	0.23
	[-1.51]	[-0.62]	[-0.49]	[0.52]	[1.37]	[1.84]
Return	1.09	2.64	2.52	2.34	5.82	8.17
Inflation	2.39	15.55	3.17	4.92	32.10	138.57
Real interest rate	4.93	7.15	7.33	7.17	7.68	17.03
Net foreign assets	16.18	-19.98	-14.40	-17.48	-33.63	-27.39
Current account	0.09	0.64	-0.10	0.93	-2.28	-1.99
GDP share	2.30	1.40	1.89	0.40	1.51	1.47
Market capitalization	53.77	31.84	54.77	49.78	60.25	31.45
Market volume	29.46	16.69	27.34	21.08	21.58	13.53
			1999-2012			
Downside beta	0.05	0.19	0.29	0.34	0.44	0.57
	[1.47]	[3.21]	[3.11]	[3.68]	[5.29]	[8.03]
Return	2.66	2.12	4.40	6.59	5.12	10.22
Inflation	3.75	3.12	3.81	6.87	3.99	7.54
Real interest rate	3.97	3.36	4.57	4.67	4.40	12.18
Net foreign assets	32.24	-6.09	-38.46	-49.10	-31.30	-52.94
Current account	3.75	-1.10	-4.92	0.18	0.90	-3.76
GDP share	1.33	1.58	2.75	1.00	1.21	1.07
Market capitalization	46.81	114.80	28.61	56.29	62.68	74.98
Market volume	19.70	98.77	20.45	40.49	53.33	46.64
Country risk	8.60	5.08	6.50	6.38	7.82	8.05

Table 4.2. Cross-sectional regressions for individual currencies

The table reports coefficients of univariate and multivariate cross-sectional regressions of currency downside betas on country's macroeconomic characteristics. The regressions are estimated for two sub-periods. A cross-section of 36 countries is considered in each sub-period. T-statistics are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: 1990-1998												
Inflation	0.03								0.03		0.03	
	[4.51]								[4.20]		[3.93]	
Real interest rate		0.31								0.22		0.25
		[3.07]								[2.66]		[2.74]
Net foreign assets			-0.14						-0.13	-0.14	-0.10	-0.12
			[-2.70]						[-2.49]	[-2.31]	[-1.34]	[-1.49]
Current account				-0.85							-0.10	-0.07
				[-1.49]							[-0.15]	[-0.10]
GDP share					-1.20						-1.11	-1.10
					[-1.54]						[-1.43]	[-1.47]
Market cap.						-0.07					0.01	0.00
						[-0.93]					[0.21]	[-0.04]
Market volume							-0.16				-0.05	-0.02
							[-1.96]				[-0.60]	[-0.21]
Intercept	0.01	0.00	0.00	0.02	0.04	0.06	0.06	-	0.00	-0.01	0.02	0.01
	[0.42]	[-0.04]	[0.05]	[0.62]	[1.08]	[0.97]	[1.26]	-	[-0.15]	[-0.37]	[0.25]	[0.13]
R2	0.10	0.08	0.15	0.07	0.03	0.04	0.08	-	0.22	0.21	0.25	0.24
R2 adj	0.07	0.05	0.13	0.04	0.00	0.01	0.05	-	0.17	0.16	0.09	0.07
Panel B: 1999-2012												
Inflation	1.66								1.40		2.16	1.61
	[2.15]								[1.86]		[2.17]	[1.44]
Real interest rate		1.15								1.04		1.14
		[6.08]								[7.12]		[5.61]
Net foreign assets			-0.09						-0.07	-0.07	-0.14	-0.14
			[-2.19]						[-1.96]	[-1.89]	[-1.51]	[-1.41]
Current account				-0.44							0.63	0.83
				[-1.16]							[0.95]	[1.16]
Size (GDP share)					-0.41						-1.05	-1.64
					[-0.57]						[-0.45]	[-0.84]
Market cap.						-0.01					0.07	0.06
						[-0.10]					[0.66]	[0.53]
Market volume							0.00				0.00	0.00
							[-0.04]				[0.03]	[-0.04]
Country risk								0.01			-0.01	-0.01
								[0.66]			[-0.67]	[-0.95]
Intercept	0.23	0.23	0.28	0.30	0.31	0.31	0.31	0.27	0.22	0.22	0.18	0.18
	[3.37]	[4.03]	[5.61]	[5.52]	[5.42]	[4.82]	[4.71]	[4.03]	[3.58]	[4.07]	[2.09]	[1.64]
R2	0.15	0.19	0.11	0.02	0.00	0.00	0.00	0.02	0.21	0.27	0.32	0.41
R2 adj	0.13	0.17	0.08	-0.01	-0.03	-0.03	-0.03	-0.01	0.16	0.22	0.14	0.21

Table 4.3. Risk characteristics of currency portfolios sortedby macroeconomic variables

The table reports downside betas and average macroeconomic characteristics of currency portfolios, sorted yearly by country's macroeconomic variables. 36 currencies are used in sub-periods 1990-1998 and 1999-2012 to form 6 equal-weighted portfolios, sorted by one macroeconomic variable at a time. HML is 6 minus 1 long-short portfolio. T-statistics are in brackets,t-statistics are calculated using Newey-West heteroskedasticity consistent standard errors. The returns, inflation and real interest rates are reported in percent per annum. Net foreign assets, current account, market capitalization and market volume are measured in percent to local GDP. GDP share is measured relative to world GDP. Country risk is proxied by Fitch country rating on a scale from 1 to 24, a higher number means higher risk.

		Panel A: 1990-2012						
		Pfl 1	**2**	**3**	**4**	**5**	**Pfl 6**	**HML**
Rates		**Sort by inflation**						
	Inflation	0.73	2.01	2.83	4.01	6.87	78.03	
	Downside beta	0.13	0.21	0.25	0.27	0.21	0.34	0.22
		[1.88]	[2.64]	[2.59]	[2.71]	[3.85]	[4.59]	[3.48]
		Sort by real interest rate						
	Real interest rate	1.98	3.49	4.55	5.81	7.26	15.08	
	Downside beta	0.13	0.18	0.19	0.20	0.24	0.34	0.21
		[1.85]	[2.25]	[3.45]	[2.38]	[3.11]	[3.46]	[3.98]
External position		**Sort by net foreign assets**						
	Net foreign assets	-89.80	-46.27	-30.51	-17.42	-4.46	62.72	
	Downside beta	0.35	0.31	0.25	0.23	0.20	0.10	-0.25
		[4.43]	[3.44]	[2.59]	[2.49]	[2.78]	[1.74]	[-3.36]
		Sort by current account						
	Current account	-8.05	-4.19	-2.18	0.12	2.80	9.85	
	Downside beta	0.23	0.29	0.33	0.23	0.20	0.16	-0.07
		[2.17]	[3.22]	[3.54]	[2.53]	[2.95]	[2.72]	[-0.95]
Size		**Sort by GDP share**						
	GDP share	0.09	0.28	0.48	0.85	2.02	5.70	
	Downside beta	0.18	0.28	0.22	0.22	0.32	0.17	-0.01
		[1.49]	[3.05]	[2.77]	[3.48]	[4.14]	[2.74]	[0.61]
		Sort by market cap						
	Market cap	11.25	21.46	34.67	50.56	79.02	147.72	
	Downside beta	0.21	0.25	0.29	0.22	0.20	0.21	0.00
		[2.36]	[2.59]	[4.20]	[2.29]	[3.49]	[2.59]	[-0.17]
		Sort by market volume						
	Market volume	1.73	5.82	13.45	30.72	56.42	112.30	
	Downside beta	0.27	0.19	0.30	0.22	0.21	0.20	-0.06
		[3.46]	[2.89]	[3.05]	[2.71]	[3.10]	[2.38]	[-1.21]

Table 4.3. Risk characteristics of currency portfolios sortedby macroeconomic variables (continued)

The table reports downside betas and average macroeconomic characteristics of currency portfolios, sorted yearly by country's macroeconomic variables. 36 currencies are used in sub-periods 1990-1998 and 1999-2012 to form 6 equal-weighted portfolios, sorted by one macroeconomic variable at a time. HML is 6 minus 1 long-short portfolio. T-statistics are in brackets,t-statistics are calculated using Newey-West heteroskedasticity consistent standard errors. The returns, inflation and real interest rates are reported in percent per annum. Net foreign assets, current account, market capitalization and market volume are measured in percent to local GDP. GDP share is measured relative to world GDP. Country risk is proxied by Fitch country rating on a scale from 1 to 24, a higher number means higher risk.

		Panel B: 1999-2012						
		Pfl 1	**2**	**3**	**4**	**5**	**Pfl 6**	**HML**
Rates		**Sort by inflation**						
	Inflation	0.52	1.97	2.82	3.92	5.90	13.94	
	Downside beta	0.18	0.32	0.38	0.38	0.28	0.48	0.30
		[3.43]	[3.10]	[4.16]	[4.00]	[4.78]	[7.24]	[5.33]
		Sort by real interest rate						
	Real interest rate	1.54	2.77	3.69	4.88	6.31	15.73	
	Downside beta	0.19	0.28	0.27	0.28	0.32	0.46	0.28
		[2.60]	[3.59]	[5.40]	[3.04]	[4.21]	[5.06]	[4.70]
External position		**Sort by net foreign assets**						
	NFA	-109.04	-51.50	-34.72	-20.00	-7.20	76.80	
	Downside beta	0.48	0.41	0.37	0.34	0.29	0.17	-0.31
		[6.92]	[4.31]	[3.75]	[3.54]	[4.03]	[3.27]	[-6.10]
		Sort by current account						
	Current account	-9.74	-5.01	-2.69	0.20	3.21	11.87	
	Downside beta	0.33	0.38	0.47	0.33	0.31	0.21	-0.12
		[2.94]	[3.98]	[5.85]	[3.54]	[5.45]	[3.56]	[-1.39]
Size		**Sort by GDP share**						
	GDP share	0.04	0.19	0.38	0.70	1.66	6.05	
	Downside beta	0.27	0.38	0.31	0.30	0.47	0.26	-0.01
		[1.92]	[3.96]	[4.23]	[4.38]	[6.79]	[5.91]	[-0.06]
		Sort by market cap						
	Market cap	11.84	23.20	38.42	56.86	89.32	164.55	
	Downside beta	0.25	0.41	0.41	0.34	0.27	0.31	0.06
		[2.11]	[4.51]	[6.68]	[3.96]	[4.90]	[4.02]	[0.36]
		Sort by market volume						
	Market volume	1.19	5.06	14.20	38.87	75.88	144.18	
	Downside beta	0.30	0.25	0.46	0.39	0.29	0.30	0.00
		[3.38]	[3.30]	[5.63]	[6.29]	[4.21]	[3.75]	[0.07]
Country risk		**Sort by country risk**						
	Range of rating	1=2	3=5	6=7	8=9	10=12	13=24	
	Downside beta	0.26	0.17	0.31	0.31	0.28	0.37	0.10
		[2.25]	[3.89]	[2.46]	[2.81]	[2.59]	[4.37]	[1.32]

Table 4.4. Risk characteristics of currency portfolios double sorted by inflation and real interest rates

The table reports downside betas and average inflation and real interest rates of 3x2 currency portfolios, double sorted annually by inflation and real interest rates. 36 currencies are used in sub-periods 1990-1998 and 1999-2012 to form 6 equal-weighted portfolios. T-statistics are in brackets,t-statistics are calculated using Newey-West heteroskedasticity consistent standard errors. Inflation and real interest rates are reported in percent per annum.

	Pfl 1	**2**	**3**	**4**	**5**	**Pfl 6**
	Low infl Low r	Low infl High r	Med infl Low r	Med infl High r	High infl Low r	High infl High r
	1990-2012					
Inflation	1.32	1.44	3.52	3.41	10.17	9.95
Real interest rate	1.56	7.41	2.86	8.41	3.10	11.47
Downside beta	0.13	0.15	0.17	0.26	0.20	0.30
	[1.79]	[2.30]	[2.27]	[2.56]	[2.86]	[4.84]
	1999-2012					
Inflation	1.24	1.30	3.50	3.43	9.44	8.48
Real interest rate	-0.12	6.44	2.03	7.72	1.98	11.48
Downside beta	0.12	0.22	0.27	0.37	0.29	0.36
	[2.40]	[3.22]	[4.07]	[3.67]	[4.05]	[5.96]

Chapter 5. Conclusion

This thesis is devoted to the study of downside risk in stock and currency markets. I show that the exposure to the downside risk can explain returns to momentum and carry trade strategies, two common investment strategies in the stock and currency markets, respectively. These strategies were thought to generate abnormal returns because if their high average returns and low average correlations with the market. I show that once we look at their *conditional* correlations with the market in states of low market returns, these strategies are very risky because they provide low returns exactly in 'hard times', when returns are particularly valuable.

In the first paper of this thesis, I show that once we separate the overall market risk of momentum portfolios into the upside and downside risks, the momentum strategies appear to have asymmetric risk profile: they are exposed to the downside risk, but hedge against the upside risk. Since the upside and downside risks are priced differently, the momentum return is a compensation for this risk asymmetry. I consider US, global and regional momentum and reversal portfolios of individual stocks and global momentum portfolios of country indices and currencies. I show that the asymmetry in upside and downside market risks explains all cross-sections of momentum portfolio returns well. Past loser portfolios have lower downside risk and higher upside risk, whereas past winner portfolios have higher downside risk and lower upside risk and, hence, greater downside-upside risk asymmetry. For any set of momentum portfolios, the risk asymmetry is monotonically increasing with portfolio rank. The downside-risk CAPM explains the cross-section of momentum returns much better than the traditional CAPM. The estimates of the relative downside beta premium are always statistically significant and similar in magnitude to the estimates obtained for other asset markets. Therefore, the momentum return is not anomalous, but a compensation for the asymmetric upside and downside market risks.

In the second paper of this thesis, I examine the global downside market risk of currencies as an explanation for the high excess returns to carry trades. I consider three alternative measures of downside risk (the downside beta, the 'disaster beta' and the coskewness) and show that these measures have high explanatory power for returns.I find that the downside market risk of currency portfolios is monotonically increasing in the local interest rate level. The returns of high-interest (investment) currencies have high downside stock market betas and 'disaster betas' and significant negative coskewness with the stock market; by contrast, the returns of low-interest (funding) currencies have insignificant downside betas and positive coskewness. The downside market beta and the coskewness have much greater explanatory power in the cross-section of currency portfolios than the traditional market beta. The GMM estimates of the downside beta and coskewness premiums are highly significant, similar in the currency and stock markets and close to the theoretical values. The downside risk is priced similarly in different markets, and the high returns to carry trades are *fair* compensation for their high downside market risk.

In the third paper of this thesis, I explore which macroeconomic characteristics are systematically related to the downside risk of currencies besides the level of nominal interest rates. I show that 'safe haven' currencies have low inflation and real interest rates and positive net foreign asset positions of the respective countries. By contrast, currencies which tend to crash with the stock market belong to debtor countries with high real interest and inflation rates. The level of the real interest rate has the highest explanatory power in the cross-section of currency exposure to the downside risk, especially in the 2000s.This suggests that there is a 'flight to quality' in the currency market in 'hard times' (i.e. capital is withdrawn from high real interest rate risky currencies of debtor countries and returned to low real interest rate 'safe haven' currencies of creditor countries). Other macroeconomic variables, previously suggested in the literature, do not seem to play a significant role in explaining currency exposure to the downside risk.

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Appendices

A1. APPENDIX TO CHAPTER 3

Samples of countries

Full sample of 42 countries: Australia, Austria, Belgium, Canada, Chile, Cyprus, Czech Republic, Denmark, Euro Zone, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Malta, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK.

Sub-sample of 15 developed countries: Australia, Belgium, Canada, Denmark, Euro Zone, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, UK.

Dates of disasters according to Ranaldo and Söderlind (2010) classification

Date	Event	Type	Date	Event	Type
12/03/1993	Storm of the Century	Nature	01/08/2003	European heat wave	Nature
20/12/1994	Tequila peso crisis	Finance	11/03/2004	Madrid bombings	Terror&war
02/07/1997	East Asian financial crisis	Finance	24/09/2004	Hurricane Rita	Nature
27/10/1997	Global stock market crash	Finance	26/12/2004	Tsunami	Nature
23/08/1998	Russian financial crisis	Finance	07/07/2005	London bombings I	Terror&war
10/03/2000	Dot-com bubble burst	Finance	27/07/2005	London bombings II	Terror&war
04/06/2001	2001 Atlantic hurricane	Nature	23/08/2005	Hurricane Katrina	Nature
11/09/2001	WTC terrorist attacks	Terror&war	08/10/2005	Kashmir earthquake	Nature
02/12/2001	Accounting scandals (Enron)	Finance	12/07/2006	Lebanon War	Terror&war
01/11/2002	SARS	Nature	27/02/2007	Sell-off of Chinese shares	Finance
20/03/2003	Second Gulf War	Terror&war	08/2007-02/2009	Global financial crisis	Finance

Source: Ranaldo and Söderlind (2010)

A2. APPENDIX TO CHAPTER 4

Samples of currencies and their respective downside betas in two sub-periods 1990-1998 and 1999-2012

Currencies are listed in order of increasing downside betas.

1990-1998		1999-2012	
Japan	-0.19	Japan	-0.09
Switzerland	-0.17	Malta	-0.02
Cyprus	-0.14	Cyprus	0.03
Malta	-0.09	Slovenia	0.09
Ireland	-0.07	Argentina	0.09
France	-0.06	Philippines	0.14
Denmark	-0.06	Thailand	0.15
Italy	-0.05	Switzerland	0.17
Spain	-0.05	UK	0.17
Belgium	-0.05	Singapore	0.18
Turkey	-0.05	Estonia	0.23
Finland	-0.05	India	0.23
Germany	-0.05	Lithuania	0.24
Portugal	-0.04	Latvia	0.25
UK	-0.04	Slovakia	0.26
Netherlands	-0.04	Denmark	0.28
Sweden	-0.03	Bulgaria	0.28
Iceland	-0.03	Euro Zone	0.29
Austria	-0.03	Czech Rep	0.29
Singapore	0.03	Russia	0.30
Philippines	0.03	Romania	0.33
Norway	0.04	Canada	0.35
Greece	0.05	Norway	0.36
New Zealand	0.07	Iceland	0.38
Thailand	0.07	Indonesia	0.39
India	0.09	South Korea	0.42
South Africa	0.09	Sweden	0.42
Argentina	0.11	Mexico	0.45
Australia	0.12	Chile	0.46
Canada	0.12	Poland	0.49
Chile	0.14	Hungary	0.49
Mexico	0.16	South Africa	0.50
South Korea	0.17	New Zealand	0.51
Brazil	0.22	Australia	0.54
Czech Rep	0.28	Brazil	0.68
Poland	0.39	Turkey	0.71