Downside Risk in Emerging Markets

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ABSTRACT

This paper investigates the relation between downside risk and expected returns on the aggregate stock market in an international context. Nonparametric and parametric Value at Risk (VaR) are used as measures of downside risk to determine the existence and significance of a risk-return tradeoff. Using market return data from 27 emerging countries, fixed-effects panel data regressions provide evidence for a significantly positive relationship between monthly expected market returns and downside risk. This result is robust after controlling for aggregate dividend yield, price-to-earnings ratio and price-to-cash flow ratio. The relationship between expected returns and downside risk is much weaker for developed markets. Indeed, it vanishes when control variables are included in the downside risk-return specification. These results continue to hold when we use a different emerging market classification system, an alternative regression methodology and exclude extreme returns.

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1. INTRODUCTION

The relationship between risk and return in the aggregate stock market has been one of the central topics in financial economics. Merton (1973) suggests that the conditional expected excess return on the aggregate market should be a linear function of the aggregate market's conditional volatility plus a hedging component which proxies for the investor's desire to hedge for future investment opportunities. Moreover, the relationship between the conditional excess return and the conditional volatility should be positive if investors are risk-averse. There have been numerous subsequent empirical studies that investigate this tradeoff between risk and return. The results from these studies that use different specifications and estimation methods have been inconclusive. Although studies such as Scruggs (1998), Ghysels, Santa-Clara and Valkanov (2005), Guo and Whitelaw (2006), Lundblad (2007) and Bali and Engle (2010) do find evidence for a risk-return tradeoff, other studies have found an insignificant (e.g., French, Schwert and Stambaugh, 1987; Baillie and DeGenarro, 1990) and even a significantly negative (e.g., Nelson, 1991; Glosten, Jagannathan and Runkle, 1993; Lettau and Ludvigson, 2002) relationship between the conditional mean and volatility of market returns.

This paper investigates the relationship between downside risk and expected returns. Value at Risk (VaR), the expected loss on the market portfolio at a given level of probability, is used to measure downside risk to determine the existence and significance of a risk-return tradeoff. Bali, Demirtas and Levy (2009) find a positive, significant and robust link between downside risk and returns on various U.S. market portfolios. This paper extends their analysis to an international cross-sectional context. We find evidence for a significantly positive link between one-month ahead expected returns and both nonparametric and parametric VaR for emerging markets. This positive link is robust to the inclusion of the aggregate dividend yield, price-to-earnings ratio and price-to-cash flow ratio in the panel regression setting as a proxy for the hedging demand. Although there is mild evidence for a risk-return tradeoff for developed markets, this finding is not robust to the inclusion of control variables in the regression specifications.

There is a myriad of reasons why we consider downside risk in determining the existence of a positive risk-return tradeoff. First, Roy (1952) introduces the idea of safety-first investors who seek to minimize their losses in case of a disaster and considers the implications of minimizing the upper bound of the probability of a dread event when the information available about the joint probability distribution of future states of nature is confined to the first- and second-order moments. Levy and Sarnat (1972) and Arzac and Bawa (1977) relate the safety-first principle to the expected utility framework. Investors who aim to maximize their expected return subject to a maximum loss constraint will reflect downside risk, as measured by VaR, to their asset valuations.

Second, the assumptions of the mean-variance analysis developed by Markowitz (1952) have been debated extensively. Mean-variance optimization can be justified under either of two assumptions. First, investors who have quadratic preferences will not be concerned about extreme losses. Alternatively, the mean and variance will completely describe the return distribution if the asset returns are jointly normally distributed. However, the empirical regularity that stock returns are typically skewed and leptokurtic has been widely documented. In other words, in reality, extreme events occur more frequently than predicted by the normal distribution. Arditti (1967), Rubinstein (1973) and Kraus and Litzenberger (1976) set up theoretical models that incorporate the effect of unconditional co-skewness in asset pricing. Harvey and Siddique (2000) introduce a similar model that focuses on the conditional co-skewness. More recently, Brunnermeir, and Parker (2005) and Barberis and Huang (2008) have proposed behavioral explanations regarding the impact of idiosyncratic skewness on asset prices. The common implication of these studies is that investors prefer positively or right-skewed investments to negatively or left-skewed investments. Therefore, assets that decrease a portfolio's skewness are less desirable and should require higher expected returns. For kurtosis, Dittmar (2002) draws on the theoretical works of Pratt and Zeckhauser (1987) and Kimball (1993) and suggests that investors have a preference for less leptokurtic investments, i.e. assets that increase a portfolio's kurtosis are less desirable and should require higher expected returns. As far as downside risk is concerned, asset distributions with more left-skewness and thicker tails have larger VaRs. Thus, we expect a significantly positive relation between VaR and expected market returns.

Finally, many financial and non-financial institutions need to quantify the amount of loss they may incur in a given period of time. Instead of doing financial projections on a best estimate basis, regulatory bodies require commercial banks to do stress testing where the robustness of their financial statements under various crash scenarios is judged. Capital adequacy is determined based on the magnitude of the potential losses if such crashes materialize. Pension funds are legally required to structure their investment portfolios such that the risk of insufficient funding is kept under a certain threshold. Credit rating agencies also monitor likely losses on company assets and incorporate this information to the ratings they issue. Due to all these factors, players in the financial markets are expected to take downside risk, as measured by VaR, into account in their investment decisions implying potential asset pricing consequences.

In our empirical analysis, for the emerging market group, univariate regressions show that there is a significantly positive relationship between nonparametric VaR and expected market returns when VaR is measured using the minimum daily returns from past return windows ranging from five months to 12 months. We also find that when control variables such as the aggregate dividend yield, price-to-earnings ratio and price-to-cash flow ratio are added to the specifications, all of the nonparametric VaR measures attain significantly positive coefficients. For the developed country group, we find a significantly positive downside risk-return tradeoff when nonparametric VaR is measured using daily return data from the most recent month. However, this finding is not robust to the inclusion of control variables in the fixed-effects panel data regressions. The parametric VaR measures that are based on the lower tail of Hansen's skewed *t*-distribution yield similar results.

The paper is organized as follows. Section 2 discusses the methodology for investigating the downside risk-return tradeoff and presents the data and summary statistics. Section 3 discusses the empirical results from the panel data regressions for emerging and developed markets separately. Section 4 concludes.

2. METHODOLOGY AND DATA

2.1 Measuring Value at Risk

2.1.1 Nonparametric Value at Risk

In order to uncover the relationship between downside risk and stock market, we first use a nonparametric measure of VaR which measures how much the value of a portfolio could decline in a fairly extreme outcome if one were to rank order possible outcomes from best to worst. In other words, VaR attempts to answer the question of how much an investor can expect to lose on a portfolio in a given time period at a given level of probability. For example, if a portfolio of equities has a one-month 5% VaR of $1 million, this means that there is a 5% probability that the portfolio value will decline more than $1 million over a one-month period. In our analysis, we use the minimum market returns observed during given past windows of daily data as of the end of each month and estimate alternative VaR measures from the lower tail of the empirical return distribution. We should note that the original VaR measures are multiplied by -1 before they are included in the regressions so that higher magnitudes of the measures correspond to greater downside risk. Therefore, we expect a positive and statistically significant relation between nonparametric VaR and the excess returns on the aggregate market portfolio.

Motivated by the lack of a significant relationship between risk and return in the earlier literature, Harrison and Zhang (1999) focus on various holding intervals longer than the sampling interval of data to see whether a significant relation between risk and return exists. Their rationale is that it is less likely for factors such as portfolio rebalancing, transaction costs and unexpected consumption needs to play an important role compared to the actual risk factor in longer horizons. In light of this idea, Ghysels, Santa-Clara and Valkanov (2005) use a larger windows that range from one to 6 months when they construct realized volatility measures by summing past squared returns to measure conditional variance. Their mixed data sampling approach uncovers a significantly positive risk-return relationship for the aggregate U.S. market index at certain horizons. Bali et al. (2009) apply this idea to their downside risk measures and find that the coefficients of these measures are greater in magnitude and statistical significance for sampling windows larger than one month. Our downside risk measure, Var_k, is calculated as the minimum daily return over varying past window lengths from 1 to 12 months. We assume that each month consists of 21 trading days. Var_1 is defined as the minimum daily return observed during the past 21 days; hence, it corresponds to 4.76% value at risk. Var_{12} is defined as the minimum daily return observed during the past 252 days; hence, it can be interpreted as 0.40% value at risk.

2.1.2 Parametric Value at Risk

To account for skewness and excess kurtosis in the data, Hansen (1994) introduces a generalization of the Student *t*-distribution where asymmetries may occur, while maintaining the assumption of a zero mean and unit variance. This skewed *t* (ST) density is given by:

$$f(z_t;\mu,\sigma,v,\lambda)=\begin{cases} bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1-\lambda}\right)^2\right)^{-\frac{v+1}{2}} & \text{if } z_t<-a/b \\ bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1+\lambda}\right)^2\right)^{-\frac{v+1}{2}} & \text{if } z_t\geq -a/b \end{cases} \tag{1}$$

where $z_t=\frac{R_t-\mu}{\sigma}$ is the standardized expected market return, and the constants *a*, *b*, and *c* are given by

$$a=4\lambda c\left(\frac{v-2}{v-1}\right) b^2=1+3\lambda^2-a^2,\ c=\frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)} \tag{2}$$

Hansen (1994) shows that this density is defined for $2 < v < \infty$ and $-1 < \lambda < 1$. This density has a single mode at $-a/b$, which is of opposite sign with the parameter λ. Thus, if $\lambda > 0$, the mode of the density is to the left of zero and the variable is skewed to the right, and vice versa when $\lambda < 0$. Furthermore, if $\lambda = 0$, Hansen's distribution reduces to the traditional standardized t distribution. If $\lambda = 0$ and $v = \infty$, it reduces to a normal density.[3]

A parametric approach to calculating VaR is based on the lower tail of the ST distribution. Specifically, we estimate the parameters of the ST density (μ, σ, υ, λ) using the past 1 to 12 months of daily data and then find the corresponding percentile of the

[3] The parameters of the ST density are estimated by maximizing the log-likelihood function of R_t with respect to the parameters μ, σ, υ and λ:

$$\log L = n\ln b + n\ln\Gamma\left(\frac{v+1}{2}\right)-\frac{n}{2}\ln\pi - n\ln\Gamma(v-2)-n\ln\Gamma\left(\frac{v}{2}\right)-n\ln\sigma-\left(\frac{v+1}{2}\right)\sum_{t=1}^{n}\ln\left(1+\frac{d_t^2}{(v-2)}\right)$$

where $d_t = (bz_t+a)/(1-\lambda s)$ and s is a sign dummy taking the value of 1 if $bz_t+a<0$ and s = -1 otherwise.

estimated distribution. Assuming that $R_t = f_{v,\lambda}(z)$ follows a ST density, parametric VaR is the solution to

$$\int_{-\infty}^{\Gamma_{ST}(\Phi)} f_{v,\lambda}(z)dz = \Phi \tag{3}$$

where $\Gamma_{ST}(\Phi)$ is the VaR threshold based on the ST density with a loss probability of Φ. Equation (3) indicates that VaR can be calculated by integrating the area under the probability density function of the ST distribution.

2.2 Estimation Methodology

We investigate the cross-sectional relationship between downside risk and stock market returns using the following fixed-effects panel data regressions:

$$R_{i,t} = \alpha_t + \beta\, Var_{k,i,t-1} + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t}$ is the excess return on country *i*'s market portfolio at month *t* and $Var_{k,i,t-1}$ is the VaR of the market portfolio in country *i* conditioned on the daily return data over the past *k* months set up to time *t-1*. We investigate whether the slope coefficient β in equation (1) is positive and statistically significant.

The fixed-effects panel regression in equation (4) allows each month over the sample period to take a different intercept. Therefore, these fixed-effects panel data regressions can be interpreted as stacked cross-sectional regressions or a collection of cross-sectional regressions for each month. This procedure ensures that each monthly data point is demeaned and each month's error term is orthogonal to the VaR measure for that particular month. Finding a significant slope coefficient would indicate that countries in which investors perceive greater downside risk for the aggregate market have higher expected aggregate returns. We follow the methodology of Rogers (1993) for computing standard errors in the presence of heteroskedasticity and contemporaneous cross-correlations. The regressions are estimated separately for emerging and developed markets. By doing so, we aim to see whether a potential link between downside risk and expected market returns exists for both, one, or none of the two country groups.

2.3 Data

Our data for daily market returns is obtained from the DataStream Global Equity Indices database. There are 52 markets for which DataStream provides daily index price information. We classify these 52 markets as either emerging or developed based on the definitions from Financial Times and London Stock Exchange (FTSE) Group, Morgan Stanley Capital International (MSCI) and Dow Jones. These three classification systems list a different set of countries as emerging markets. Our main analysis takes the union set of the emerging market definitions by these three classification systems and treats them as emerging markets. As a result, the final sample consists of 27 emerging markets.[4] These countries are Argentina, Brazil, Bulgaria, Chile, China, Colombia, Czech Republic, Hong Kong, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Romania, Russia, Singapore, South Africa, South Korea, Sri Lanka, Taiwan, Thailand, Turkey and Venezuela. The remaining 25 countries from DataStream

[4] In robustness tests, we take only the intersection test of the definitions from the classification systems and apply our analysis to this reduced set of emerging markets. The results are presented in Section 3.5.

are classified as developed markets. These countries are Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland Republic, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, United Kingdom and United States. The sample period ends at January 2011 for each market; however, the beginning period differs due to the data that are available in DataStream. On average, there are 313 months per country. The exact sample period for each market is presented in the Appendix.

We use the total market index item named *TOTMK* as the national market index for each country. *TOTMK* series is a value-weighted index where weightings are allocated on the basis of market capitalization. We use the Return Index (RI) associated with *TOTMK* to construct the daily return series since it reflects the index values with dividends and distributions. We also use the price data in terms of local currencies to construct the returns because we do not want currency risk to contaminate the analysis. The monthly index returns are calculated by compounding daily returns. Later in the analysis, we use the aggregate dividend yield (DY), price-to-earnings ratio (PE) and price-to-cash flow ratio (PC) as control variables in the fixed-effects panel data regressions. The data for all these variables also come from DataStream.

2.4 Summary Statistics

Table 1 presents the summary statistics for monthly returns and nonparametric VaR measures for the stock market indices.[5] The summary statistics are presented separately

[5] To conserve space, we do not report summary statistics associated with parametric VaR measures. The distribution of parametric VaR is similar to that of nonparametric VaR and the results are available from the authors upon request.

for emerging and developed country groups. The table presents the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, maximum, skewness and kurtosis statistics for the returns and downside risk measures for the pooled sample of monthly observations for each group. Panels A and B present summary statistics for the emerging and developed markets, respectively.

The summary statistics for the monthly returns of emerging markets are presented in the first row of Panel A of Table 1. The mean monthly return for the pooled sample of emerging markets is 1.78 percent and the corresponding standard deviation is 9.61 percent indicating substantial dispersion. To get a better feel for the existence of extreme swings, we look at the minimum and maximum monthly returns. The minimum and maximum monthly returns are -45.77 percent and 84.95 percent, respectively, indicating dramatic losses or gains in particular months. The 25th and 75th percentiles of the monthly return distributions are much closer to the mean and are equal to -3.12 percent and 6.34 percent, respectively. The median monthly return is 1.48 percent. Given the proximity of the mean and median monthly returns, the lack of a substantial asymmetry in the return distribution is not surprising. The skewness statistic of 0.90 indicates that the emerging market monthly returns were right-skewed, but only mildly. Also, given the extreme losses and gains that some markets experienced over the sample period, the kurtosis statistic turns out to be high with a value of 9.83. The first row of Panel B presents similar statistics for the pooled sample of monthly developed market returns. The standard deviation of 6.12 percent is about six times the mean return of 1.00 percent also indicating significant dispersion in monthly developed market returns. However, the mean return and its standard deviation for developed markets are smaller than those for emerging markets reflecting the fact that emerging markets are affected by more risk factors. The minimum and maximum monthly returns of -40.24 percent and 72.19 percent point out that extreme stock market swings are also encountered in developed markets; however, their magnitudes are smaller than those in emerging markets. The median return is 1.16 percent which is only slightly higher than the mean. The lack of distributional asymmetry is also evident from the small skewness statistic of 0.44. Finally, the kurtosis statistic for developed market returns is 10.74.

The second row of both panels present summary statistics for VaR_1, the monthly nonparametric VaR measure calculated based on the minimum daily returns over the most recent month. Panel A shows that the mean value for this downside risk measure is equal to 2.74 percent for the emerging market sample implying that the 4.76% value at risk over 21 trading days has been -2.74 percent over the sample period, on average. The standard deviation of VaR_1 is equal to 2.21 percent and lower than the mean. The minimum VaR_1 has been -0.02 percent. This means that there exists a country-month for which the minimum daily return over the past 21 trading days has been 0.02 percent. The maximum VaR_1 is 41.10 percent which corresponds to the lowest daily return encountered during the sample period for the emerging country group. The median VaR_1 is equal to 2.16 percent and lower than the mean statistic. The skewness statistic of 3.41 indicates substantial right skewness and the kurtosis statistic of 26.65 indicates that VaR_1 measure is highly leptokurtic. As we investigate the summary statistics for other downside risk measures, several regularities become apparent. First, as the sampling window increases, the means of the downside risk measures mechanically increase. Second, the standard deviations also increase for longer sampling windows; however, the rate of increase in the standard deviations is smaller than that in the means. This indicates a relative decrease in the dispersion of the downside risk measures for longer return windows. Third, the median VaRs are still smaller than the mean VaRs, thus the bulk of the VaR distributions still lies to the left-hand side of the means. However, the degree of non-normality of the distributions gets progressively less pronounced as the sampling window increases due to the time diversification effects of skewness and kurtosis.

The rows starting with the second in Panel B of Table 1 present summary statistics for the nonparametric VaR measures for developed markets. Most of the conclusions drawn from the emerging markets also hold for the developed markets. The only difference between the VaR measures between the two country groups is that the means, standard deviations and various percentiles are smaller for the developed markets. This indicates that the magnitudes of the negative swings encountered in developed markets tend to be smaller than those in emerging markets.

3. EMPIRICAL RESULTS

3.1 Cross-Sectional Relation between Nonparametric Value at Risk and Return

The results for the fixed-effects regressions in equation (4) are presented in Table 2. Panel A presents the results for the pooled sample of emerging markets, whereas Panel B presents results for developed markets. The first column indicates the number of past months for which the minimum daily return is used to construct the nonparametric VaR measures. The second column presents the regression intercepts and their clustered *t*-statistics. The coefficients associated with the VaR measures and their clustered *t*-statistics are presented in the third column. The fourth and fifth columns indicate the total number of observations and the average number of observations per country, respectively.

The first regression that includes VaR_1 as an explanatory variable shows that this particular measure of downside risk has a significant relation with expected market returns at the 5% level for the emerging country group. The coefficient of VaR_1 is 0.2064 with an associated clustered *t*-statistic of 1.98. When the sampling window for daily returns is extended to two months, the magnitude of the coefficient and its *t*-statistic decrease. The coefficient of VaR_2 is 0.1418 and it is only significant at the 10% level. For the three- and four-month sampling horizons, the coefficients of the downside risk measures continue to drop. However, at the five-month window, the coefficient again becomes significantly positive with a *t*-statistic of 2.09. The results show that as the sampling window is increased even further, the *t*-statistics for the coefficients of the downside risk measures continue to increase and the relationship between risk and return gets sharper. For the remaining regressions that use VaR_6 to VaR_{12}, the coefficients of downside risk measures remain significant. The highest *t*-statistic of 2.73 is attained at the eight-month window. As we use the minimum daily return from windows ranging from past nine to 12 months to construct the VaR measures, the magnitude and statistical significance of the coefficients decrease. The R^2s vary between 31.76% and 33.65% with the highest R^2 observed at the nine-month window. To summarize, the results from Table

2 indicate that there is a positive and statistically significant relationship between downside risk and expected market returns across countries among the emerging market group.

Panel B of Table 1 presents results for the developed market group. The results in this panel are in sharp contrast to those found for the emerging market group. In the first regression, VaR_1 has a coefficient of 0.1856 with a clustered t-statistic of 2.19. At the two-month horizon, the coefficient of the downside risk measure drops to 0.1458 but it is just significant at the 5% level with a t-statistic of 1.96. As the sampling window for past daily returns is extended, the t-statistics for the VaR measures continue to decrease almost monotonically. None of the VaR measures from VaR_3 to VaR_{12} have significant coefficients.

3.2 Controlling For Dividend Yield, Price-to Earnings and Price-to-Cash Flow

One of the most prominent market multiples that has been identified in the literature as a determinant of expected equity returns is the dividend yield (Fama and French, 1988; Hodrick, 1992). Campbell and Shiller (1988) develop a log-linear approximation of equity returns which provides a framework to examine the relationship between dividend yields and expected returns. Besides the dividend yield, some recent papers such as Bollerslev, Zhou and Tauchen (2009) find that price-to-earnings ratio, the reciprocal of the earnings yield, has a significantly negative relation with expected market returns. Therefore, we control for the dividend yield and the price-to-earnings ratio when we investigate the relationship between downside risk and expected international market returns. We also include the price-to-cash flow variable as an additional control in our specifications. The number of total observations drops somewhat in this analysis because the data for the control variables start at a later date than that for the index returns.

The results for the emerging country group are presented in Panel A of Table 3. We find that, after controlling for all three variables, all the nonparametric VaR measures have a positive and statistically significant relation with aggregate returns. The *t*-statistics for the downside risk measures increase almost monotonically as the sampling window is extended from one to 9 months. The highest statistical significance is attained for the nine-month sampling window. The coefficient of VaR_9 is 0.1984 with a *t*-statistic of 3.69. When the sampling window is extended even more, the magnitude and statistical significance of the coefficients decrease. However, even VaR_{12} loads significantly with a *t*-statistic of 3.33. These results indicate that the significantly positive relation between downside risk and expected market returns for the emerging country sample is not driven by the omission of the control variables from the specifications. All three control variables have statistically significant coefficients for all sampling windows. The *t*-statistics vary between 3.97 and 4.26, -3.56 and -3.89, and -2.01 and -2.25 for the dividend yield, price-to-earnings ratio and price-to-cash flow ratio, respectively.

The results presented for the developed market sample in Panel B of Table 3 indicate that the significantly positive relationship between downside risk and aggregate returns for short sampling windows in Table 2 is not robust to the inclusion of additional controls. The coefficient of VaR_1 decreases to 0.0278 with a *t*-statistic of 0.28. None of the VaR measures load significantly in the regressions and the coefficients turn negative in seven of the twelve regressions. We conclude that there is no robust link between downside risk and expected market returns in the developed country sample. Although the dividend yield and price-to-earnings ratio have insignificant coefficients in all the specifications, the *t*-statistics for the price-to-cash flow range from -2.78 and -3.04 indicating a robust relationship between this variable and expected market returns.

3.3 Cross-Sectional Relation between Parametric Value at Risk and Return

Next, we repeat the analysis in Tables 2 and 3 by using parametric VaR rather than nonparametric VaR to measure downside risk. Table 4 presents the results for the univariate fixed-effects panel data regressions. Panel A presents results for the emerging country group. The coefficient of the parametric VaR measure based on the daily returns from the most recent month is 0.1894 with a *t*-statistic of 2.12. The coefficient for VaR_3 goes down to 0.1172 and it becomes only marginally significant with a *t*-statistic of 1.64. However, the magnitude and significance of parametric VaR again increases at the five month sampling window with a *t*-statistic of 2.02. After this, all the downside risk measures are significant at least at the 5% level until the sampling window of 11 months. The highest significance is attained at the nine month window and VaR_9 has a coefficient of 0.1030 and a *t*-statistic of 2.96. The R^2's of the regressions for the emerging country group vary between 31.77% and 33.66%. When we focus on the results for the developed country group in Panel B, we see that none of the parametric VaR measures are statistically significant and the *t*-statistics range from -0.84 to 1.42.

We get similar results when we add dividend yield, price-to-earnings ratio and price-to-cash flow ratio as control variables to the specifications that include parametric VaR to measure downside risk. The results are presented in Table 5. Panel A shows that all parametric VaR measures have positive and significant coefficients in the presence of the controls. The highest significance is again attained at the nine month sampling window where VaR_9 has a coefficient of 0.1788 and a *t*-statistic of 3.69. Dividend yield has a positive coefficient whereas price-to-earnings ratio has a negative coefficient for all sampling windows, both significant at the 1% level. Price-to-cash flow ratio has a negative coefficient that is significant at the 5% level in all specifications. For the developed country group, the results are presented in Panel B of Table 5. Again, none of the parametric VaR measures have significant coefficients and the *t*-statistics vary between -1.41 and 0.58. Similar to the findings of Table 3, price-to-cash flow ratio loads negatively and significantly in all specifications.

3.4 Fama-Macbeth Regressions

In our earlier analysis, we use fixed-effects regressions in which we estimate a separate intercept coefficient for each time period. These regressions correspond to stacked cross-sectional regressions since the error terms are orthogonal to the explanatory variables in each month. One drawback of this method is the existence of contemporaneous cross-sectional correlations, thus we use clustered error terms to calculate the *t*-statistics. In this section, we use an alternative method by running Fama-Macbeth (1973) regressions. In other words, we estimate a separate regression for each time period and report the mean of each coefficient and Newey-West (1987) adjusted *t*-statistics based on the standard error of the distribution of coefficients. The results for both country groupings are presented in Table 6.[6]

Panel A of the table reports results for the emerging markets. Similar to the stacked cross-sectional regressions, we find that there is a statistically significant relation between VaR and expected market returns. The relation gets stronger after the 5-month VaR measurement horizon. The *t*-statistics for VaR_5 and VaR_{12} are 2.19 and 2.80, respectively. Panel B of the table reports the results for the developed markets. Similar to the previous conclusions, coefficient estimates at every horizon is statistically insignificant. The *t*-statistics change between 0.10 and 1.32. When we repeat all of our analysis using parametric VaR instead of nonparametric VaR, we obtain qualitatively very similar results. Our conclusion is that the significant relation between VaR and expected market returns holds for the emerging market group but does not extend to developed markets.

3.5 Alternative Set of Emerging Markets

In our main analysis, we refer to the emerging market classifications of Financial Times and London Stock Exchange (FTSE) Group, Morgan Stanley Capital International (MSCI) and Dow Jones and treat the union set of these classifications as the emerging market group. In this section, we use a more restrictive definition of an emerging market and treat only the intersection set of the classifications as emerging markets. This classification procedure reduces the number of emerging markets from 27 to 17. The new

[6] For this analysis, we impose the requirement that at least 20 countries are present in each cross-section so that the coefficient estimates make sense. Thus, the analysis for the emerging markets starts from August 1993 whereas that for the developed markets starts from January 1990.

set of emerging markets includes Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand and Turkey. In Table 7, the nonparametric VaR analysis is repeated for only these 17 countries. In the univariate regressions of Panel A, we find that nonparametric VaR has a significantly positive coefficient at the 5% level when it is measured using the minimum daily returns from past return windows ranging from 5 to 12 months. The highest significance is attained at for VaR_8 with a t-statistic of 2.72. Panel B shows that these results also hold for the multivariate setting where dividend yield, price-to-earnings ratio and price-to-cash flow ratio are included as additional explanatory variables. We find that the coefficients of dividend yield and price-to-cash flow ratio continue to be statistically significant whereas the negative relation between price-to-earnings ratio and expected market returns vanishes. More importantly, there is still a significantly positive relation between VaR and expected market returns at the 5% level in all measurement windows beginning from the 5-month horizon and the highest statistical significance is attained at the 8-month horizon with a t-statistic of 2.62. These results show that the significant downside risk-return tradeoff uncovered in Tables 2 and 3 continue to hold for a more restricted set of emerging markets.

3.6 Excluding Extreme Returns in 1997

Our sample period includes the Asian financial crisis in 1997 which has hit many Asian markets badly and caused worldwide fears of economic instability amidst the possibility of financial contagion. It is possible that our results are affected by the extreme negative returns that occurred during this period as our emerging sample group includes markets such as Thailand, Indonesia, South Korea, Philippines and Malaysia; and our VaR measures are extracted from the left tail of the return distribution.

To control for the effects of this period, we carry out two different analyses. First, we truncate the sample of monthly returns during 1997 by excluding the highest and lowest 5% of the returns. Descriptive statistics show that the 5^{th} and 95^{th} percentiles of the monthly returns during this sample period correspond to -17.19% and 18.65%, respectively. After excluding these extreme returns, Panel A of Table 8 shows that VaR_1 has a positive and significant relation with expected market returns at the 5% level. Although the significance is reduced initially as the VaR measurement window extends, the significantly positive relation once again reappears for VaR_5 and continues to hold until the 12-month measurement window. The highest significance is attained at the 8-month window with a *t*-statistic of 2.60. Second, we delete all the monthly observations during 1997 to see whether our results are robust to excluding this tumultuous period for the world economy. Panel B of Table 8 shows that the significant relation between nonparametric *VaR* and expected market returns is somewhat reduced, however there is still a significantly positive relation at the 5% level starting from the 7-month measurement window. The coefficient on VaR_8 is 0.1153 with a *t*-statistic of 2.52. These results collectively suggest that the significant tradeoff between downside risk and expected market returns is robust to excluding the extreme returns encountered during the 1997 Asian financial crisis.

4. CONCLUSION

We investigate the cross-sectional relation between downside risk and expected returns for emerging and developed markets. Recent developments in the world financial markets once more proved the importance of downside risk in portfolio allocation. Although there are many studies which examine the relation between traditional risk measures as well as downside risk measures and expected returns in US, there is lack of evidence regarding the link between downside risk and expected returns in emerging markets.

In this paper, we utilize fixed-effects panel data regressions and investigate the cross-sectional relation between expected market returns and downside risk. This investigation is repeated for emerging and developed markets separately. We measure downside risk by nonparametric and parametric value at risk. The results show that there is a statistically significant relation between VaR and expected returns in emerging markets. This relation is stronger when VaR is computed using a larger set of data. In developed markets, the relation between expected returns and VaR is much weaker. Indeed, any significance that is found at short intervals is washed away by the inclusion of control variables. On the other hand, in emerging markets, the significant relation between downside risk and expected returns remains robust when control variables are added to the estimations. These results continue to hold when we use a different emerging market classification system, an alternative regression methodology and exclude extreme returns.

We conclude that higher return moments are important determinants of expected returns in emerging markets such that emerging market countries with higher expected downside risk have higher risk premia.

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Table 1. Summary Statistics for Emerging and Developed Markets

This table presents descriptive statistics for the pooled sample of monthly returns and nonparametric Value at Risk (VaR) for the emerging and developing stock market indices. Panel A presents descriptive statistics for emerging markets. Panel B presents descriptive statistics for developed markets. *R* is the monthly return compounded from daily aggregate returns. VaR_k is defined as -1 times the minimum daily index return observed during the last *k* months. Each month is assumed to consist of 21 trading days. Measures of VaR are presented for different horizons ranging from one month to 12 months. The descriptive statistics that are presented in the table are the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, maximum, skewness, and kurtosis.

Panel A. Monthly Statistics for Emerging Markets

Variable	Mean	Std. Dev.	Minimum	25-percentile	Median	75-percentile	Maximum	Skewness	Kurtosis
R	0.01783	0.09606	-0.45771	-0.03124	0.01480	0.06343	0.84949	0.90359	9.83411
VaR_1	0.02741	0.02214	-0.00022	0.01366	0.02159	0.03403	0.41101	3.41275	26.65250
VaR_2	0.03495	0.02646	0.00094	0.01859	0.02800	0.04240	0.41101	3.45933	26.95762
VaR_3	0.03994	0.02890	0.00546	0.02188	0.03247	0.04848	0.41101	3.24713	23.19528
VaR_4	0.04381	0.03055	0.00721	0.02450	0.03568	0.05356	0.41101	3.06232	20.62804
VaR_5	0.04707	0.03192	0.00763	0.02677	0.03890	0.05746	0.41101	2.93445	18.93326
VaR_6	0.04989	0.03308	0.00792	0.02899	0.04139	0.06059	0.41101	2.83022	17.66976
VaR_7	0.05243	0.03412	0.00946	0.03079	0.04364	0.06414	0.41101	2.74922	16.66506
VaR_8	0.05467	0.03501	0.00978	0.03220	0.04572	0.06696	0.41101	2.68494	15.93238
VaR_9	0.05671	0.03566	0.00978	0.03374	0.04804	0.06953	0.41101	2.61262	15.28944
VaR_{10}	0.05857	0.03623	0.00978	0.03443	0.04922	0.07211	0.41101	2.55783	14.80247
VaR_{11}	0.06027	0.03680	0.00978	0.03584	0.05089	0.07393	0.41101	2.51465	14.39304
VaR_{12}	0.06180	0.03736	0.01296	0.03719	0.05316	0.07540	0.41101	2.47885	14.02127

Panel B. Monthly Statistics for Developed Markets

Variable	Mean	Std. Dev.	Minimum	25-percentile	Median	75-percentile	Maximum	Skewness	Kurtosis
R	0.00998	0.06123	-0.40242	-0.02133	0.01152	0.04257	0.72187	0.43543	10.73782
VaR_1	0.01924	0.01480	-0.00165	0.00997	0.01536	0.02378	0.25492	3.12193	23.45735
VaR_2	0.02422	0.01719	-0.00018	0.01350	0.01984	0.02934	0.25492	2.98446	20.90177
VaR_3	0.02758	0.01885	0.00000	0.01567	0.02264	0.03292	0.25492	2.87084	19.10598
VaR_4	0.03021	0.02014	0.00000	0.01738	0.02492	0.03639	0.25492	2.76366	17.76100
VaR_5	0.03251	0.02126	0.00000	0.01881	0.02699	0.03965	0.25492	2.66795	16.58000
VaR_6	0.03446	0.02218	0.00062	0.02004	0.02842	0.04210	0.25492	2.59273	15.75113
VaR_7	0.03623	0.02300	0.00322	0.02127	0.02994	0.04417	0.25492	2.52830	15.03189
VaR_8	0.03779	0.02375	0.00364	0.02232	0.03131	0.04663	0.25492	2.46729	14.39527
VaR_9	0.03925	0.02441	0.00758	0.02322	0.03252	0.04859	0.25492	2.41485	13.88400
VaR_{10}	0.04055	0.02500	0.00758	0.02391	0.03379	0.04984	0.25492	2.37385	13.47680
VaR_{11}	0.04173	0.02553	0.00758	0.02473	0.03502	0.05126	0.25492	2.34263	13.15627
VaR_{12}	0.04281	0.02597	0.00758	0.02549	0.03607	0.05238	0.25492	2.30774	12.86045

Table 2. Cross Sectional Relation between Nonparametric Value at Risk and Return

This table presents the relationship between one-month ahead expected market returns and nonparametric Value at Risk (VaR) in a fixed-effects panel data regression setting. The intercepts are allowed to take different values for each month. VaR_k is defined as -1 times the minimum daily index return observed during the last k months. Panels A and B present results for emerging and developed markets, respectively. The first column indicates the number of past months for which daily returns are used to construct the VaR measures. The second column presents the intercepts and their clustered t-statistics in parentheses. The third column presents the coefficients associated with VaR and their clustered t-statistics in parentheses. The fourth and fifth columns indicate the total number of observations and the average number of observations per country, respectively. The last column presents R^2s. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Cross Sectional Regressions for Emerging Markets

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0120	0.2064	6,962	257.9	0.3176
	(4.20)[a]	(1.98)[b]			
2	0.0125	0.1418	6,936	256.9	0.3210
	(4.44)[a]	(1.77)[c]			
3	0.0128	0.1128	6,912	256.0	0.3205
	(4.44)[a]	(1.56)			
4	0.0133	0.0918	6,887	255.1	0.3240
	(5.39)[a]	(1.63)			
5	0.0120	0.1112	6,860	254.1	0.3266
	(4.77)[a]	(2.09)[b]			
6	0.0123	0.0995	6,833	253.1	0.3276
	(4.99)[a]	(2.02)[b]			
7	0.0113	0.1165	6,806	252.1	0.3279
	(4.53)[a]	(2.46)[b]			
8	0.0109	0.1206	6,781	251.1	0.3339
	(4.49)[a]	(2.73)[a]			
9	0.0111	0.1097	6,757	250.3	0.3365
	(4.67)[a]	(2.61)[a]			
10	0.0121	0.0870	6,731	249.3	0.3363
	(5.34)[a]	(2.25)[b]			
11	0.0123	0.0843	6,704	248.3	0.3348
	(5.33)[a]	(2.20)[b]			
12	0.0124	0.0826	6,677	247.3	0.3355
	(5.38)[a]	(2.21)[b]			

Panel B. Stacked Cross Sectional Regressions for Developed Markets

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0064	0.1856	9,339	373.6	0.4681
	(3.94)[a]	(2.19)[b]			
2	0.0065	0.1458	9,308	372.3	0.4696
	(3.59)[a]	(1.96)[b]			
3	0.0073	0.0982	9,292	371.7	0.4695
	(4.11)[a]	(1.52)			
4	0.0071	0.0958	9,268	370.7	0.4758
	(4.01)[a]	(1.64)			
5	0.0066	0.1027	9,243	369.7	0.4766
	(3.69)[a]	(1.86)[c]			
6	0.0071	0.0834	9,218	368.7	0.4806
	(3.87)[a]	(1.57)			
7	0.0070	0.0825	9,193	367.7	0.4822
	(3.72)[a]	(1.59)			
8	0.0076	0.0661	9,168	366.7	0.4808
	(4.04)[a]	(1.33)			
9	0.0080	0.0521	9,143	365.7	0.4811
	(4.28)[a]	(1.09)			
10	0.0087	0.0340	9,118	364.7	0.4824
	(4.55)[a]	(0.72)			
11	0.0092	0.0257	9,093	363.7	0.4811
	(4.85)[a]	(0.57)			
12	0.0095	0.0174	9,068	362.7	0.4816
	(5.06)[a]	(0.40)			

Table 3. Controlling for Dividend Yield, Price-to-Earnings and Price-to-Cash Flow in the Presence of Nonparametric VaR

This table presents the results for the regression of one-month ahead expected market returns on nonparametric Value at Risk (VaR), dividend yield (DY), price-to-earnings ratio (PE) and price-to-cash flow ratio (PC) in a fixed-effects panel data regression setting. The intercepts are allowed to take different values for each month. VaR_k is defined as -1 times the minimum daily index return observed during the last k months. Panels A and B present results for emerging and developed markets, respectively. The first column indicates the number of past months for which daily returns are used to construct VaR measures. The second column presents the intercepts and their clustered t-statistics in parentheses. The third columns presents the coefficients associated with VaR and their clustered t-statistics in parentheses. The fourth, fifth and sixth columns presents the coefficients associated with DY, PE and PC, respectively and their clustered t-statistics in parentheses. The seventh and eighth columns indicate the total number of observations and the average number of observations per country, respectively. The last column presents R^2s. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Cross Sectional Regressions for Emerging Markets

Lags	Constant	VaR	DY	PE	PC	Total # of observations	Average # of observations	R^2
1	0.0150	0.1971	0.0037	-0.0008	-0.0003	5,469	202.6	0.3590
	(2.80)[a]	(2.03)[b]	(4.00)[a]	(-3.88)[a]	(-2.05)[b]			
2	0.0138	0.1942	0.0037	-0.0008	-0.0003	5,463	202.3	0.3596
	(2.54)[b]	(2.24)[b]	(4.00)[a]	(-3.88)[a]	(-2.01)[b]			
3	0.0136	0.1734	0.0037	-0.0008	-0.0003	5,458	202.1	0.3595
	(2.53)[b]	(2.23)[b]	(4.02)[a]	(-3.88)[a]	(-2.04)[b]			
4	0.0126	0.1914	0.0037	-0.0008	-0.0003	5,452	201.9	0.3599
	(2.33)[b]	(2.69)[a]	(3.97)[a]	(-3.89)[a]	(-2.07)[b]			
5	0.0114	0.1933	0.0037	-0.0008	-0.0003	5,446	201.7	0.3596
	(2.13)[b]	(3.01)[a]	(4.00)[a]	(-3.82)[a]	(-2.09)[b]			
6	0.0115	0.1790	0.0038	-0.0008	-0.0003	5,440	201.5	0.3594
	(2.20)[b]	(2.97)[a]	(4.03)[a]	(-3.81)[a]	(-2.13)[b]			
7	0.0111	0.1851	0.0038	-0.0008	-0.0003	5,434	201.3	0.3592
	(2.17)[b]	(3.26)[a]	(4.05)[a]	(-3.82)[a]	(-2.19)[b]			
8	0.0101	0.1973	0.0038	-0.0008	-0.0003	5,426	201.0	0.3607
	(1.95)[c]	(3.53)[a]	(4.04)[a]	(-3.85)[a]	(-2.25)[b]			
9	0.0088	0.1984	0.0039	-0.0008	-0.0003	5,418	200.7	0.3623
	(1.72)[c]	(3.69)[a]	(4.21)[a]	(-3.69)[a]	(-2.25)[b]			
10	0.0087	0.1776	0.0040	-0.0007	-0.0003	5,410	200.4	0.3626
	(1.73)[c]	(3.56)[a]	(4.26)[a]	(-3.56)[a]	(-2.23)[b]			
11	0.0092	0.1685	0.0040	-0.0007	-0.0003	5,402	200.1	0.3624
	(1.82)[c]	(3.50)[a]	(4.24)[a]	(-3.60)[a]	(-2.25)[b]			
12	0.0097	0.1556	0.0040	-0.0007	-0.0003	5,394	199.8	0.3624
	(1.91)[c]	(3.33)[a]	(4.19)[a]	(-3.58)[a]	(-2.22)[b]			

Panel B. Stacked Cross Sectional Regressions for Developed Markets

Lags	Constant	VaR	DY	PE	PC	Total # of observations	Average # of observations	R^2
1	0.0150	0.0278	0.0008	-0.0002	-0.0009	6,151	246.0	0.5538
	(3.80)[a]	(0.28)	(1.01)	(-1.64)	(-3.04)[a]			
2	0.0155	-0.0086	0.0008	-0.0002	-0.0009	6,145	245.8	0.5548
	(3.90)[a]	(-0.10)	(1.08)	(-1.65)[c]	(-3.02)[a]			
3	0.0152	0.0030	0.0008	-0.0002	-0.0009	6,144	245.8	0.5549
	(3.73)[a]	(0.04)	(1.11)	(-1.69)[c]	(-3.01)[a]			
4	0.0140	0.0103	0.0010	-0.0002	-0.0008	6,140	245.6	0.5655
	(3.35)[a]	(0.15)	(1.34)	(-1.67)[c]	(-2.82)[a]			
5	0.0140	0.0118	0.0010	-0.0002	-0.0008	6,136	245.4	0.5659
	(3.35)[a]	(0.18)	(1.30)	(-1.66)[c]	(-2.81)[a]			
6	0.0154	-0.0289	0.0011	-0.0002	-0.0008	6,132	245.3	0.5719
	(3.75)[a]	(-0.45)	(1.42)	(-1.77)[c]	(-2.84)[a]			
7	0.0152	-0.0204	0.0010	-0.0002	-0.0008	6,128	245.1	0.5722
	(3.52)[a]	(-0.31)	(1.37)	(-1.75)[c]	(-2.85)[a]			
8	0.0153	-0.0233	0.0011	-0.0002	-0.0008	6,124	245.0	0.5722
	(3.53)[a]	(-0.37)	(1.43)	(-1.72)[c]	(-2.89)[a]			
9	0.0156	-0.0313	0.0011	-0.0002	-0.0008	6,120	244.8	0.5718
	(3.56)[a]	(-0.50)	(1.44)	(-1.71)[c]	(-2.90)[a]			
10	0.0161	-0.0370	0.0010	-0.0002	-0.0008	6,116	244.6	0.5726
	(3.65)[a]	(-0.61)	(1.29)	(-1.75)[c]	(-2.83)[a]			
11	0.0165	-0.0403	0.0009	-0.0002	-0.0008	6,112	244.5	0.5730
	(3.72)[a]	(-0.67)	(1.24)	(-1.79)[c]	(-2.79)[a]			
12	0.0163	-0.0369	0.0010	-0.0002	-0.0008	6,108	244.3	0.5732
	(3.68)[a]	(-0.63)	(1.27)	(-1.80)[c]	(-2.78)[a]			

Table 4. Cross Sectional Relation between Parametric Value at Risk and Return

This table presents the relationship between one-month ahead expected market returns and parametric Value at Risk (VaR) in a fixed-effects panel data regression setting. The intercepts are allowed to take different values for each month. VaR_k is defined as the appropriate percentile of Hansen's (1994) skewed t-density estimated using the past k months of daily data. Panels A and B present results for emerging and developed markets, respectively. The first column indicates the number of past months for which daily returns are used to construct the VaR measures. The second column presents the intercepts and their clustered t-statistics in parentheses. The third column presents the coefficients associated with VaR and their clustered t-statistics in parentheses. The fourth and fifth columns indicate the total number of observations and the average number of observations per country, respectively. The last column presents R^2s. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Cross Sectional Regressions for Emerging Markets

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0121	0.1894	6,962	27	0.3177
	(4.57)[a]	(2.12)[b]			
2	0.0135	0.1187	6,936	27	0.3207
	(4.67)[a]	(1.37)			
3	0.0131	0.1172	6,912	27	0.3205
	(5.15)[a]	(1.64)[c]			
4	0.0143	0.0810	6,887	27	0.3238
	(7.09)[a]	(1.51)			
5	0.0133	0.1003	6,860	27	0.3264
	(6.93)[a]	(2.06)[b]			
6	0.0137	0.0868	6,833	27	0.3275
	(7.52)[a]	(1.93)[c]			
7	0.0128	0.1093	6,806	27	0.3279
	(7.38)[a]	(2.65)[a]			
8	0.0130	0.1044	6,781	27	0.3337
	(7.73)[a]	(2.68)[a]			
9	0.0128	0.1030	6,757	27	0.3366
	(8.34)[a]	(2.96)[a]			
10	0.0141	0.0691	6,731	27	0.3361
	(10.26)[a]	(2.27)[b]			
11	0.0146	0.0616	6,704	27	0.3345
	(10.57)[a]	(2.05)[b]			
12	0.0150	0.0539	6,677	27	0.3351
	(10.69)[a]	(1.79)[c]			

Panel B. Stacked Cross Sectional Regressions for Developed Markets

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0078 (5.15)[a]	0.1033 (1.42)	9,339	25	0.4674
2	0.0095 (6.12)[a]	0.0227 (0.34)	9,308	25	0.4688
3	0.0111 (6.70)[a]	-0.0419 (-0.63)	9,292	25	0.4691
4	0.0114 (6.80)[a]	-0.0540 (-0.84)	9,268	25	0.4754
5	0.0109 (6.51)[a]	-0.0327 (-0.54)	9,243	25	0.4760
6	0.0104 (6.22)[a]	-0.0141 (-0.24)	9,218	25	0.4801
7	0.0098 (5.70)[a]	0.0062 (0.11)	9,193	25	0.4817
8	0.0096 (5.52)[a]	0.0170 (0.29)	9,168	25	0.4805
9	0.0100 (5.92)[a]	0.0034 (0.06)	9,143	25	0.4809
10	0.0107 (6.39)[a]	-0.0209 (-0.39)	9,118	25	0.4823
11	0.0109 (6.36)[a]	-0.0203 (-0.38)	9,093	25	0.4810
12	0.0114 (6.69)[a]	-0.0358 (-0.68)	9,068	25	0.4817

Table 5. Controlling for Dividend Yield, Price-to-Earnings and Price-to-Cash Flow in the Presence of Parametric VaR

This table presents the results for the regression of one-month ahead expected market returns on parametric Value at Risk (VaR), dividend yield (DY), price-to-earnings ratio (PE) and price-to-cash flow ratio (PC) in a fixed-effects panel data regression setting. The intercepts are allowed to take different values for each month. VaR_k is defined as the appropriate percentile of Hansen's (1994) skewed t-density estimated using the past k months of daily data. Panels A and B present results for emerging and developed markets, respectively. The first column indicates the number of past months for which daily returns are used to construct VaR measures. The second column presents the intercepts and their clustered *t*-statistics in parentheses. The third columns presents the coefficients associated with VaR and their clustered *t*-statistics in parentheses. The fourth, fifth and sixth columns presents the coefficients associated with DY, PE and PC, respectively and their clustered *t*-statistics in parentheses. The seventh and eighth columns indicate the total number of observations and the average number of observations per country, respectively. The last column presents R^2s. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Cross Sectional Regressions for Emerging Markets

Lags	Constant	VaR	DY	PE	PC	Total # of observations	Average # of observations	R^2
1	0.0152	0.1724	0.0038	-0.0008	-0.0003	5,469	202.6	0.3589
	(2.87)[a]	(2.01)[b]	(4.00)[a]	(-3.85)[a]	(-2.06)[b]			
2	0.0145	0.1775	0.0037	-0.0008	-0.0003	5,463	202.3	0.3593
	(2.73)[a]	(2.09)[b]	(3.99)[a]	(-3.85)[a]	(-2.03)[b]			
3	0.0147	0.1575	0.0037	-0.0008	-0.0003	5,458	202.1	0.3592
	(2.92)[a]	(2.11)[b]	(4.01)[a]	(-3.83)[a]	(-2.06)[b]			
4	0.0142	0.1701	0.0037	-0.0008	-0.0003	5,452	201.9	0.3594
	(2.86)[a]	(2.56)[b]	(3.95)[a]	(-3.83)[a]	(-2.09)[b]			
5	0.0135	0.1693	0.0037	-0.0008	-0.0003	5,446	201.7	0.3590
	(2.71)[a]	(2.76)[a]	(3.98)[a]	(-3.76)[a]	(-2.11)[b]			
6	0.0138	0.1544	0.0037	-0.0008	-0.0003	5,440	201.5	0.3588
	(2.83)[a]	(2.59)[a]	(4.00)[a]	(-3.76)[a]	(-2.13)[b]			
7	0.0137	0.1607	0.0037	-0.0008	-0.0003	5,434	201.3	0.3584
	(2.90)[a]	(2.90)[a]	(4.00)[a]	(-3.78)[a]	(-2.16)[b]			
8	0.0132	0.1723	0.0037	-0.0008	-0.0003	5,426	201.0	0.3597
	(2.74)[a]	(3.03)[a]	(3.97)[a]	(-3.80)[a]	(-2.19)[b]			
9	0.0119	0.1788	0.0039	-0.0007	-0.0003	5,418	200.7	0.3613
	(1.72)	(3.69)[a]	(4.21)[a]	(-3.69)[a]	(-2.25)[b]			
10	0.0122	0.1495	0.0040	-0.0007	-0.0003	5,410	200.4	0.3615
	(2.58)[a]	(3.04)[a]	(4.16)[a]	(-3.53)[a]	(-2.14)[b]			
11	0.0131	0.1349	0.0040	-0.0007	-0.0003	5,402	200.1	0.3612
	(2.77)[a]	(2.80)[a]	(4.14)[a]	(-3.57)[a]	(-2.16)[b]			
12	0.0140	0.1127	0.0039	-0.0007	-0.0003	5,394	199.8	0.3611
	(2.92)[a]	(2.34)[b]	(4.09)[a]	(-3.57)[a]	(-2.12)[b]			

Panel B. Stacked Cross Sectional Regressions for Developed Markets

Lags	Constant	VaR	DY	PE	PC	Total # of observations	Average # of observations	R^2
1	0.0143 (3.60)[a]	0.0545 (0.58)	0.0008 (1.03)	-0.0002 (-1.64)[c]	-0.0009 (-3.06)[a]	6,151	246.0	0.5539
2	0.0162 (3.90)[a]	-0.0353 (-0.41)	0.0008 (1.06)	-0.0002 (-1.65)[c]	-0.0009 (-3.00)[a]	6,145	245.8	0.5548
3	0.0164 (4.01)[a]	-0.0413 (-0.49)	0.0008 (1.07)	-0.0002 (-1.68)[c]	-0.0008 (-2.98)[a]	6,144	245.8	0.5550
4	0.0153 (3.69)[a]	-0.0349 (-0.43)	0.0010 (1.29)	-0.0002 (-1.67)[c]	-0.0008 (-2.78) [a]	6,140	245.6	0.5655
5	0.0155 (3.70)[a]	-0.0372 (-0.46)	0.0009 (1.24)	-0.0002 (-1.67)[c]	-0.0008 (-2.78)[a]	6,136	245.4	0.5659
6	0.0168 (4.03)[a]	-0.0785 (-1.00)	0.0010 (1.36)	-0.0002 (-1.78)[c]	-0.0008 (-2.82)[a]	6,132	245.3	0.5721
7	0.0165 (3.82)[a]	-0.0653 (-0.81)	0.0010 (1.32)	-0.0002 (-1.77)[c]	-0.0008 (-2.82)[a]	6,128	245.1	0.5723
8	0.0169 (3.90)[a]	-0.0765 (-1.00)	0.0010 (1.36)	-0.0002 (-1.75)[c]	-0.0008 (-2.85)[a]	6,124	245.0	0.5724
9	0.0171 (3.93)[a]	-0.0829 (-1.09)	0.0010 (1.37)	-0.0002 (-1.74)[c]	-0.0008 (-2.87)[a]	6,120	244.8	0.5720
10	0.0175 (4.01)[a]	-0.0841 (-1.16)	0.0009 (1.23)	-0.0002 (-1.79)[c]	-0.0008 (-2.79)[a]	6,116	244.6	0.5729
11	0.0179 (4.13)[a]	-0.0913 (-1.27)	0.0009 (1.18)	-0.0002 (-1.84)[c]	-0.0008 (-2.75)[a]	6,112	244.5	0.5733
12	0.0181 (4.21)[a]	-0.0983 (-1.41)	0.0009 (1.18)	-0.0002 (-1.86)[c]	-0.0008 (-2.72)[a]	6,108	244.3	0.5736

Table 6. Fama-Macbeth Regressions

This table presents the relationship between one-month ahead expected market returns and nonparametric Value at Risk (VaR) in a Fama-Macbeth (1973) regression setting. VaR_k is defined as -1 times the minimum daily index return observed during the last k months. Panels A and B present results for emerging and developed markets, respectively. The first column indicates the number of past months for which daily returns are used to construct the VaR measures. The second column presents the intercepts and their clustered t-statistics in parentheses. The third column presents the coefficients associated with VaR and their Newey-West (1987) adjusted t-statistics in parentheses. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Cross Sectional Regressions for Emerging Markets

Lags	Constant	VaR
1	0.0106	0.1824
	(2.08)[b]	(1.94)[c]
2	0.0091	0.1831
	(1.85)[c]	(2.12)[b]
3	0.0074	0.2040
	(1.46)	(2.20)[b]
4	0.0081	0.1607
	(1.54)	(1.77)[c]
5	0.0071	0.1809
	(1.38)	(2.19)[b]
6	0.0071	0.1788
	(1.45	(2.50)[b]
7	0.0070	0.1811
	(1.42)	(2.71)[a]
8	0.0061	0.1951
	(1.19)	(2.75)[a]
9	0.0058	0.1911
	(1.08)	(2.52)[b]
10	0.0062	0.1880
	(1.16)	(2.44)[b]
11	0.0060	0.1890
	(1.14)	(2.60)[a]
12	0.0056	0.1869
	(1.09)	(2.80)[a]

Panel B. Stacked Cross Sectional Regressions for Developed Markets

Lags	Constant	VaR
1	0.0058	0.1758
	(1.87)[c]	(1.08)
2	0.0051	0.1840
	(1.51)	(1.32)
3	0.0066	0.0894
	(1.99)[b]	(0.81)
4	0.0066	0.0818
	(2.22)[b]	(0.83)
5	0.0074	0.0517
	(2.33)[b]	(0.52)
6	0.0077	0.0449
	(2.65)[a]	(0.50)
7	0.0071	0.0363
	(2.33)[b]	(0.47)
8	0.0072	0.0417
	(2.26)[b]	(0.55)
9	0.0085	0.0074
	(2.60)[a]	(0.10)
10	0.0082	0.0252
	(2.35)[b]	(0.32)
11	0.0076	0.0304
	(2.19)[b]	(0.41)
12	0.0074	0.0348
	(2.15)[b]	(0.46)

Table 7. Alternative Set of Emerging Markets

In this table, the set of emerging markets is reduced to the intersection set of the classification systems of Financial Times and London Stock Exchange (FTSE) Group, Morgan Stanley Capital International (MSCI) and Dow Jones. This set includes Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand and Turkey. Panel A presents the results for the univariate regressions of one-month ahead expected market returns on nonparametric Value at Risk (VaR). Panel B presents the results for a multivariate fixed-effects panel data regression setting which includes dividend yield (DY), price-to-earnings ratio (PE) and price-to-cash flow ratio (PC) as additional explanatory variables. The intercepts are allowed to take different values for each month. VaR_k is defined as -1 times the minimum daily index return observed during the last k months. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Stacked Univariate Cross Sectional Regressions

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0131 (4.48)[a]	0.2063 (1.90)[c]	4,243	249.6	0.3734
2	0.0134 (4.03)[a]	0.1515 (1.55)	4,228	248.7	0.3760
3	0.0148 (4.03)[a]	0.0940 (0.99)	4,213	247.8	0.3753
4	0.0128 (3.38)[a]	0.1365 (1.52)	4,198	246.9	0.3760
5	0.0109 (2.78)[a]	0.1689 (1.96)[b]	4,181	245.9	0.3761
6	0.0109 (2.78)[a]	0.1606 (1.97)[b]	4,164	244.9	0.3772
7	0.0103 (2.62)[a]	0.1689 (2.17)[b]	4,147	243.9	0.3759
8	0.0084 (2.16)[b]	0.2009 (2.72)[a]	4,131	243.0	0.3786
9	0.0098 (2.48)[b]	0.1647 (2.27)[b]	4,116	242.1	0.3796
10	0.0100 (2.67)[a]	0.1539 (2.32)[b]	4,100	241.2	0.3788
11	0.0105 (2.80)[a]	0.1433 (2.20)[b]	4,083	240.2	0.3779
12	0.0109 (2.88)[a]	0.1343 (2.10)[b]	4,066	239.2	0.3788

Panel B. Stacked Multivariate Cross Sectional Regressions

Lags	Constant	VaR	DY	PE	PC	Total # of observations	Average # of observations	R^2
1	0.0337 (4.47)[a]	0.1918 (1.68)[c]	0.0028 (2.37)[b]	0.0000 (-0.13)	-0.0038 (-4.81)[a]	3,743	220.2	0.3730
2	0.0333 (4.36)[a]	0.1622 (1.52)	0.0028 (2.38)[b]	-0.0001 (-0.19)	-0.0038 (-4.77)[a]	3,739	219.9	0.3729
3	0.0332 (4.21)[a]	0.1459 (1.44)	0.0028 (2.37)[b]	-0.0001 (-0.19)	-0.0038 (-4.78)[a]	3,736	219.8	0.3729
4	0.0326 (4.04)[a]	0.1698 (1.82)[c]	0.0027 (2.27)[b]	-0.0001 (-0.22)	-0.0038 (-4.88)[a]	3,732	219.5	0.3737
5	0.0313 (3.87)[a]	0.1770 (2.08)[b]	0.0027 (2.30)[b]	0.0000 (-0.16)	-0.0038 (-4.83)[a]	3,728	219.3	0.3743
6	0.0313 (3.92)[a]	0.1711 (2.16)[b]	0.0027 (2.29)[b]	0.0000 (-0.17)	-0.0038 (-4.82)[a]	3,724	219.1	0.3745
7	0.0316 (3.98)[a]	0.1739 (2.29)[b]	0.0027 (2.26)[b]	-0.0001 (-0.21)	-0.0039 (-4.88)[a]	3,720	218.8	0.3733
8	0.0304 (3.77)[a]	0.1945 (2.62)[a]	0.0027 (2.24)[b]	-0.0001 (-0.25)	-0.0039 (-4.90)[a]	3,714	218.5	0.3757
9	0.0289 (3.62)[a]	0.1812 (2.52)[b]	0.0030 (2.47)[b]	-0.0001 (-0.21)	-0.0038 (-4.82)[a]	3,708	218.1	0.3769
10	0.0277 (3.46)[a]	0.1681 (2.49)[b]	0.0032 (2.63)[a]	-0.0001 (-0.22)	-0.0037 (-4.69)[a]	3,702	217.8	0.3773
11	0.0289 (3.70)[a]	0.1571 (2.44)[b]	0.0032 (2.60)[a]	-0.0001 (-0.21)	-0.0038 (-4.88)[a]	3,696	217.4	0.3769
12	0.0296 (3.79)[a]	0.1429 (2.27)[b]	0.0031 (2.53)[b]	-0.0001 (-0.23)	-0.0038 (-4.84)[a]	3,690	217.1	0.3770

Table 8. Excluding Extreme Return Months in 1997

In this table, we exclude extreme returns in 1997 from the emerging market group to control for the effect of the Asian financial crisis on our results. Panel A presents the results for the univariate regressions of one-month ahead expected market returns on nonparametric Value at Risk (VaR) after truncating the highest and lowest 5% of the monthly returns during 1997. Panel B presents the results for the univariate regressions of one-month ahead expected market returns on nonparametric Value at Risk (VaR) after excluding all of the monthly returns from 1997. The intercepts are allowed to take different values for each month. VaR_k is defined as -1 times the minimum daily index return observed during the last k months. [a], [b] and [c] represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Excluding the Highest and Lowest 5% of Monthly Returns During 1997

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0118	0.2140	6,932	256.7	0.3193
	(4.07)[a]	(2.01)[b]			
2	0.0124	0.1456	6,907	255.8	0.3215
	(4.32)[a]	(1.76)[c]			
3	0.0127	0.1165	6,884	255.0	0.3211
	(4.33)[a]	(1.57)			
4	0.0132	0.0947	6,859	254.0	0.3246
	(5.26)[a]	(1.64)[c]			
5	0.0121	0.1108	6,833	253.1	0.3272
	(4.74)[a]	(2.05)[b]			
6	0.0124	0.0986	6,806	252.1	0.3282
	(4.97)[a]	(1.97)[b]			
7	0.0116	0.1116	6,780	251.1	0.3283
	(4.64)[a]	(2.34)[b]			
8	0.0112	0.1159	6,755	250.2	0.3343
	(4.59)[a]	(2.60)[a]			
9	0.0114	0.1055	6,731	249.3	0.3370
	(4.76)[a]	(2.49)[b]			
10	0.0124	0.0828	6,705	248.3	0.3366
	(5.45)[a]	(2.13)[b]			
11	0.0126	0.0800	6,678	247.3	0.3352
	(5.44)[a]	(2.07)[b]			
12	0.0127	0.0787	6,651	246.3	0.3359
	(5.49)[a]	(2.10)[b]			

Panel B. Excluding All of the Monthly Returns During 1997

Lags	Constant	VaR	Total # of observations	Average # of observations	R^2
1	0.0148 (6.61)[a]	0.1259 (1.53)	6,662	246.7	0.3264
2	0.0152 (6.47)[a]	0.0798 (1.17)	6,637	245.8	0.3294
3	0.0154 (6.16)[a]	0.0624 (0.98)	6,614	245.0	0.3291
4	0.0145 (5.75)[a]	0.0820 (1.42)	6,590	244.1	0.3296
5	0.0133 (5.21)[a]	0.0994 (1.83)[c]	6,564	243.1	0.3323
6	0.0131 (5.08)[a]	0.0988 (1.90)[c]	6,538	242.1	0.3334
7	0.0123 (4.75)[a]	0.1115 (2.25)[b]	6,512	241.2	0.3335
8	0.0119 (4.76)[a]	0.1153 (2.52)[b]	6,487	240.3	0.3399
9	0.0121 (4.93)[a]	0.1060 (2.45)[b]	6,464	239.4	0.3427
10	0.0134 (5.81)[a]	0.0771 (1.96)[b]	6,439	238.5	0.3421
11	0.0136 (5.80)[a]	0.0748 (1.93)[c]	6,413	237.5	0.3406
12	0.0139 (5.93)[a]	0.0691 (1.83)[c]	6,387	236.6	0.3414

Appendix. Sample Period for Each Market

This table details the sample period for each emerging and developed market investigated in the study.

EMERGING MARKETS

Country Name	Beginning Date	Ending Date
Argentina	August 1993	January 2011
Brazil	August 1994	January 2011
Bulgaria	October 2000	January 2011
Chile	August 1989	January 2011
China	August 1993	January 2011
Colombia	April 1992	January 2011
Czech Republic	December 1993	January 2011
Hong Kong	January 1973	January 2011
Hungary	July 1991	January 2011
India	January 1990	January 2011
Indonesia	May 1990	January 2011
Malaysia	January 1986	January 2011
Mexico	June 1989	January 2011
Pakistan	August 1992	January 2011
Peru	February 1994	January 2011
Philippines	October 1987	January 2011
Poland	March 1994	January 2011
Romania	January 1997	January 2011
Russia	February 1998	January 2011
Singapore	January 1973	January 2011
South Africa	January 1973	January 2011
South Korea	October 1987	January 2011
Sri Lanka	June 1987	January 2011
Taiwan	May 1988	January 2011
Thailand	February 1987	January 2011
Turkey	February 1988	January 2011
Venezuela	January 1990	January 2011

DEVELOPED MARKETS

Country Name	Beginning Date	Ending Date
Australia	January 1973	January 2011
Austria	January 1973	January 2011
Belgium	January 1973	January 2011
Canada	January 1973	January 2011
Cyprus	January 1993	January 2011
Denmark	January 1973	January 2011
Finland	April 1988	January 2011
France	January 1973	January 2011
Germany	January 1973	January 2011
Greece	January 1990	January 2011
Ireland	January 1973	January 2011
Israel	February 1993	January 2011
Italy	January 1973	January 2011
Japan	January 1973	January 2011
Luxembourg	January 1992	January 2011
Netherlands	January 1973	January 2011
New Zealand	February 1988	January 2011
Norway	January 1980	January 2011
Portugal	January 1990	January 2011
Slovenia	January 1990	January 2011
Spain	March 1987	January 2011
Sweden	February 1982	January 2011
Switzerland	January 1973	January 2011
United Kingdom	February 1965	January 2011
United States	January 1973	January 2011