Emerging Markets Review 3 (2002) 365–379

EMERGING MARKETS REVIEW

www.elsevier.com/locate/econbase

Systematic risk in emerging markets: the D-CAPM

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Received 31 January 2002; accepted 30 June 2002

Abstract

There is by now a growing literature arguing against the use of the CAPM to estimate required returns on equity in emerging markets (EMs). One of the characteristics of this model is that it measures risk by beta, which follows from an equilibrium in which investors display mean–variance behavior. In that framework, risk is assessed by the variance of returns, a questionable and restrictive measure of risk. The semivariance of returns is a more plausible measure of risk and can be used to generate an alternative behavioral hypothesis (mean–semivariance behavior), an alternative measure of risk for diversified investors (the downside beta), and an alternative pricing model (the downside CAPM, or D-CAPM for short). The empirical evidence discussed below for the entire Morgan Stanley Capital Indices database of EMs clearly supports the downside beta and the D-CAPM over beta and the CAPM.

Keywords: Emerging markets; Semivariance; D-CAPM

1. Introduction

For over 30 years academics and practitioners have been debating the merits of the CAPM, focusing on whether beta is an appropriate measure of risk. Most of these discussions are by and large empirical; i.e. they focus on comparing the ability of beta to explain the cross-section of returns relative to that of alternative risk variables. Most of these discussions, however, overlook where beta as a measure of

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PII: S1566-0141(02)00042-0

risk comes from, namely, from an equilibrium in which investors display mean–variance behavior (MVB). In other words, the CAPM stems from an equilibrium in which investors maximize a utility function that depends on the mean and variance of returns of their portfolio.

The variance of returns, however, is a questionable measure of risk for at least two reasons: First, it is an appropriate measure of risk only when the underlying distribution of returns is symmetric. And second, it can be applied straightforwardly as a risk measure only when the underlying distribution of returns is normal. However, both the symmetry and the normality of stock returns are seriously questioned by the empirical evidence on the subject.

The semivariance of returns, on the other hand, is a more plausible measure of risk for several reasons: First, investors obviously do not dislike upside volatility; they only dislike downside volatility. Second, the semivariance is more useful than the variance when the underlying distribution of returns is asymmetric and just as useful when the underlying distribution is symmetric; in other words, the semivariance is at least as useful a measure of risk as the variance. And third, the semivariance combines into one measure the information provided by two statistics, variance and skewness, thus making it possible to use a one-factor model to estimate required returns.

Furthermore, the semivariance of returns can be used to generate an alternative behavioral hypothesis, namely, mean–semivariance behavior (MSB). As shown in Estrada (2002b), MSB is almost perfectly correlated with expected utility (and with the utility of expected compound return) and can therefore be defended along the same lines used by Levy and Markowitz (1979), Markowitz (1991) to defend MVB.

This article isolates and discusses the results specific to emerging markets (EMs) reported in Estrada (2002c), and proposes an alternative measure of risk (the downside beta) and an alternative pricing model (the downside CAPM, or D-CAPM for short). It also reports evidence supporting the downside beta over beta (and, therefore, the D-CAPM over the CAPM), and argues that the differences in required returns on equity generated by these two models are too large for practitioners to ignore or even take lightly.

The rest of the article is organized as follows. Section 2 discusses the theoretical framework by drawing a parallel between MVB and the CAPM on the hand, and MSB and the D-CAPM on the other hand. Section 3 reports and discusses the empirical evidence, which clearly supports the downside beta and, by extension, the D-CAPM and MSB. Finally, Section 4 contains some concluding remarks. The appendix concludes the article.

2. Formal framework: the D-CAPM

I discuss in this part, borrowed almost entirely from Estrada (2002c), first, the traditional MVB framework, the pricing model it follows from it (the CAPM), and the relevant magnitudes of this framework. Then I discuss the alternative MSB framework, the pricing model it follows from it and proposed in this article (the D-

CAPM), and the relevant magnitudes of this alternative framework. Then I briefly discuss how to estimate the downside beta, the magnitude proposed in this article to replace beta. And, finally, I briefly compare the D-CAPM with previous models based on downside risk proposed in the literature.

2.1. MVB and the CAPM

In the standard MVB framework, an investor's utility (U) is fully determined by the mean (μ_p) and variance (σ_p^2) of returns of the investor's portfolio; i.e. $U = U(\mu_p, \sigma_p^2)$. In such framework, the risk of an asset i taken individually is measured by the asset's standard deviation of returns (σ_i), which is given by

$$\sigma_i = \sqrt{E\left[(R_i - \mu_i)^2\right]}, \tag{1}$$

where R and μ represent returns and mean returns, respectively. However, when asset i is just one out of many in a fully diversified portfolio, its risk is measured by its covariance with respect to the market portfolio (σ_{iM}), which is given by

$$\sigma_{iM} = E\left[(R_i - \mu_i)(R_M - \mu_M)\right], \tag{2}$$

where M indexes the market portfolio. Because the covariance is both unbounded and scale-dependent, its interpretation is not straightforward. A more useful measure of risk can be obtained by dividing this covariance by the product of asset i's standard deviation of returns and the market's standard deviation of returns, thus obtaining asset i's correlation with respect to the market (ρ_{iM}), which is given by

$$\rho_{iM} = \frac{\sigma_{iM}}{\sigma_i \sigma_M} = \frac{E\left[(R_i - \mu_i)(R_M - \mu_M)\right]}{\sqrt{E\left[(R_i - \mu_i)^2\right] E\left[(R_M - \mu_M)^2\right]}}. \tag{3}$$

Alternatively, the covariance between asset i and the market portfolio can be divided by the variance of the market portfolio, thus obtaining asset i's beta (β_i), which is given by

$$\beta_i = \frac{\sigma_{iM}}{\sigma_M^2} = \frac{E\left[(R_i - \mu_i)(R_M - \mu_M)\right]}{E\left[(R_M - \mu_M)^2\right]}. \tag{4}$$

This beta can also be expressed as $\beta_i = (\sigma_i / \sigma_M)\rho_{iM}$ and is the most widely used measure of risk. It is also the only firm-specific magnitude in the model most widely used to estimate required returns on equity, the CAPM, which is given by

$$E(R_i) = R_f + \text{MRP}\beta_i, \tag{5}$$

where $E(R_i)$ and R_f denote the required return on asset i and the risk-free rate, respectively, and MRP denotes the market risk premium, defined as $\text{MRP} = E(R_M) - R_f$, where $E(R_M)$ denotes the required return on the market.

2.2. MSB and the D-CAPM

In the alternative MSB framework, the investor's utility is given by $U=U(\mu_p, \Sigma_p^2)$, where Σ_p^2 denotes the *downside* variance of returns (or semivariance for short) of the investor's portfolio. In this framework, the risk of an asset i taken individually is measured by the asset's *downside* standard deviation of returns, or semideviation (Σ_i) for short, which is given by

$$\Sigma_i = \sqrt{E\left\{\text{Min}\left[(R_i-\mu_i),0\right]^2\right\}}. \tag{6}$$

Eq. (6) is, in fact, a special case of the semideviation, which can be more generally expressed with respect to any benchmark return B (Σ_{Bi}) as

$$\Sigma_{Bi} = \sqrt{E\left\{\text{Min}\left[(R_i-B),0\right]^2\right\}}. \tag{7}$$

Given that throughout this article we will use as the only benchmark for asset i the arithmetic mean of its distribution of returns, we will denote the semideviation of asset i simply as Σ_i.

In a downside risk framework, the counterpart of asset i's covariance to the market portfolio is given by its downside covariance, or cosemivariance (Σ_{iM}) for short, which is given by

$$\Sigma_{iM} = E\left\{\text{Min}\left[(R_i-\mu_i),0\right]\text{Min}\left[(R_M-\mu_M),0\right]\right\}. \tag{8}$$

This cosemivariance is also unbounded and scale-dependent, but it can also be standardized by dividing it by the product of asset i's semideviation of returns and the market's semideviation of returns, thus obtaining asset i's downside correlation (Θ_{iM}), which is given by

$$\Theta_{iM} = \frac{\Sigma_{iM}}{\Sigma_i\Sigma_M} = \frac{E\left\{\text{Min}\left[(R_i-\mu_i),0\right]\text{Min}\left[(R_M-\mu_M),0\right]\right\}}{\sqrt{E\left\{\text{Min}\left[(R_i-\mu_i),0\right]^2\right\}E\left\{\text{Min}\left[(R_M-\mu_M),0\right]^2\right\}}}. \tag{9}$$

Alternatively, the cosemivariance can be divided by the market's semivariance of returns, thus obtaining asset i's *downside beta* (β_i^D), which is given by

$$\beta_i^D = \frac{\Sigma_{iM}}{\Sigma_M^2} = \frac{E\left\{\text{Min}\left[(R_i-\mu_i),0\right]\text{Min}\left[(R_M-\mu_M),0\right]\right\}}{E\left\{\text{Min}\left[(R_M-\mu_M),0\right]^2\right\}}. \tag{10}$$

This downside beta, which can also be expressed as $\beta_i^D=(\Sigma_i/\Sigma_M)\Theta_{iM}$, can be articulated into a CAPM-like model based on downside risk. Such model, which is the one proposed in this article, is the downside CAPM, or D-CAPM for short, and is given by

$$E(R_i) = R_f + \text{MRP}\beta_i^D. \tag{11}$$

As can be seen by a straightforward comparison of Eqs. (5) and (11), the D-

CAPM replaces the beta of the CAPM by the downside beta, the appropriate measure of systematic risk in a downside risk framework.

2.3. A brief digression on the downside beta

The downside beta of any asset i given by Eq. (10) can be estimated in at least three ways: First, by dividing the cosemivariance between asset i and the market given by Eq. (8) by the semivariance of the market given by Eq. (6) for $i=M$; i.e. $\beta_i^D = \Sigma_{iM}/\Sigma_M^2$. Alternatively, it can be estimated by multiplying the ratio of semideviations of asset i and the market, the former given by Eq. (6) and the latter given by Eq. (6) for $i=M$, by the downside correlation between asset i and the market, given by Eq. (9); i.e. $\beta_i^D = (\Sigma_i/\Sigma_M)\Theta_{iM}$. Both estimates are mathematically equivalent due to the fact that $\Theta_{iM} = \Sigma_{iM}/(\Sigma_i\Sigma_M)$; hence, $\beta_i^D = \Sigma_{iM}/\Sigma_M^2 = \Sigma_i\Sigma_M\Theta_{iM}/\Sigma_M^2 = (\Sigma_i/\Sigma_M)\Theta_{iM}$.

Finally, the downside beta of any asset i can be estimated using regression analysis, although this estimation is a bit tricky for the following reason. Let $y_t = \text{Min}[(R_{it} - \mu_i),0]$ and $x_t = \text{Min}[(R_{Mt} - \mu_M),0]$, and let μ_y and μ_x be the mean of y_t and the mean of x_t, respectively. If a regression is run with y_t as the dependent variable and x_t as the independent variable (i.e. $y_t = \lambda_0 + \lambda_1 x_t + \varepsilon_t$, where ε is an error term and λ_0 and λ_1 are coefficients to be estimated), the estimate of λ_1 would be given by

$$\lambda_1 = \frac{E[(x_t - \mu_x)(y_t - \mu_y)]}{E[(x_t - \mu_x)^2]}. \tag{12}$$

However, note that according to Eq. (10), β_i^D should be given by

$$\beta_i^D = \frac{E[x_t y_t]}{E[x_t^2]}. \tag{13}$$

In words, the appropriate way to estimate β_i^D using regression analysis is to run a simple linear regression *without a constant* between the dependent variable $y_t = \text{Min}[(R_{it} - \mu_i),0]$ and the independent variable $x_t = \text{Min}[(R_{Mt} - \mu_M),0]$, and obtaining the downside beta as the slope of such regression; i.e. run $y_t = \lambda_1 x_t + \varepsilon_t$, and obtain $\beta_i^D = \lambda_1$.

2.4. A brief digression on the downside risk framework

Hogan and Warren (1974), Bawa and Lindenberg (1977), Harlow and Rao (1989) all proposed CAPM-like models based on downside risk measures. Hogan and Warren (1974) called their framework the E-S model and defined a downside beta based on a different definition of cosemivariance; their cosemivariance (Σ_{iM}^{HW}) is given by

$$\Sigma_{iM}^{HW} = E\{(R_i - R_f)\text{Min}[(R_M - R_f),0]\}. \tag{14}$$

There are three main differences between Eqs. (14) and (8). First, under Eq. (8), a security adds to the risk of a portfolio only when $R_i < \mu_i$ and $R_M < \mu_M$; under Eq. (14), a security adds to the risk of a portfolio when $R_i < \mu_i$ and $R_M < \mu_M$, but reduces the risk of the portfolio when $R_i > \mu_i$ and $R_M < \mu_M$. Second, the benchmark return in Eq. (14) is the risk-free rate, whereas the benchmark return in Eq. (8) is the mean of each relevant distribution. And third, under Eq. (14), the cosemivariance between any two assets *i* and *j* is different from the cosemivariance between assets *j* and *i*, which is an obvious weakness of this definition of cosemivariance.[1]

Bawa and Lindenberg (1977) generalize the Hogan–Warren framework and show that, since the CAPM is a special case of their mean-lower partial moment (MLPM) model, their model is guaranteed to explain the data at least as well as the CAPM. In the Bawa–Lindenberg framework, just like in the Hogan–Warren framework, the risk-free rate is the benchmark return in the cosemivariance, and the cosemivariance between any two assets *i* and *j* is different from that between assets *j* and *i*.

Finally, Harlow and Rao (1989) derive an MLPM model for any arbitrary benchmark return, thus rendering the Hogan–Warren and the Bawa–Lindenberg frameworks special cases of their more general model. Their empirical tests reject the CAPM as a pricing model but cannot reject their version of the MLPM model. Interestingly, they argue that the relevant benchmark return that seems to be implied by the data is the mean of the distribution of returns rather than the risk-free rate.

More recently, Estrada (2000, 2001, 2002a) proposed to replace the CAPM beta by the ratio between an asset's semideviation of returns and the market's semideviation of returns, and showed that this measure of *total* downside risk explains the cross section of returns of EMs, industries in EMs, and Internet stocks. The main difference between the measure of risk proposed in those three articles, the semideviation, and the one proposed here, the downside beta, is that the downside beta is a measure of *systematic* downside risk. For a review of some of the models proposed to estimate required returns on equity in EMs, see Estrada (2000), Pereiro (2001). For a general review of downside risk see Nawrocki (1999), Sortino and Satchell (2001).

3. Empirical evidence

The data used in this article are the Morgan Stanley Capital Indices database of EMs available at the end of the year 2001. This database contains monthly data on 27 EMs for varied sample periods, some that go as far back as Jan/1988, and some that start later. Summary statistics for all markets, together with the earliest month for which data are available for each market, are reported in Table A1 in the appendix.

3.1. Statistical significance: cross-section analysis

The first step of the analysis consists of computing, over the whole sample period considered for each market, one statistic that summarizes the average (return)

[1] The main problem with the Hogan–Warren definition of cosemivariance is that, if the cosemivariance between assets *i* and *j* is different from that between assets *j* and *i*, then it is far from clear how the contribution of each of these two assets to cosemivariance risk should be interpreted. Levkoff (1982) provides a numerical example illustrating the asymmetry between these two cosemivariances.

Table 1
Cross-section analysis (simple regressions)

$MR_i = \gamma_0 + \gamma_1 RV_i + u_i$						
RV	γ_0	t-stat	γ_1	t-stat	R^2	Adj-R^2
σ	−0.79	−1.81	0.16	4.79	0.48	0.46
β	0.11	0.34	1.14	3.75	0.36	0.33
Σ	−1.01	−2.20	0.28	5.00	0.50	0.48
β^D	−0.80	−2.11	1.42	5.57	0.55	0.54

MR, mean return; RV, risk variable; σ, standard deviation; β, beta (with respect to the world market); Σ, semideviation; β^D, downside beta (with respect to the world market). Critical value for a two-sided test at the 5% significance level: 2.06.

performance of each market, and another number that summarizes its risk under each of the four definitions discussed below. Average returns over the whole sample period are summarized by mean monthly arithmetic returns; these estimates are reported in Table A1.

The four risk variables considered are two for the standard MVB framework (the standard deviation and beta) and two for the alternative MSB framework (the semideviation and downside beta), all four as defined above. An estimate of each of these four variables for each of the 27 markets in the sample is computed over the whole sample period considered for each market; these estimates are also reported in Table A1.[2]

I start by running a cross-sectional simple linear regression model relating mean returns to each of the four risk variables considered. More precisely,

$$MR_i = \gamma_0 + \gamma_1 RV_i + u_i, \tag{15}$$

where MR_i and RV_i stand for mean return and risk variable, respectively, γ_0 and γ_1 are coefficients to be estimated, u_i is an error term, and i indexes markets. The results of the four regression models (one for each of the four risk variables considered) are reported in Table 1.

As the table shows, all four risk variables are clearly significant and explain no less than one third of the variability in the cross section of returns. The downside risk measures are the two best-performing variables in terms of explanatory power, and the downside beta, in particular, explains a whopping 55% of the variability in mean returns.

Table 2 shows the results of cross-sectional multiple regression models, the first two grouping the two measures of total risk, on the one hand, and the two measures of systematic risk, on the other; i.e.

$$MR_i = \gamma_0 + \gamma_1 RV_{1i} + \gamma_2 RV_{2i} + \upsilon_i, \tag{16}$$

where RV_1 and RV_2 stand for the first and second risk variable, respectively, in each of the two models estimated. Table 2 also shows the results of a cross-sectional

[2] Semideviations and downside betas for all emerging markets are periodically updated in (and can be downloaded from) the 'Emerging Markets' link of my Web page (http://web.iese.edu/jestrada).

Table 2
Cross-section analysis (multiple regressions)

Panel A: $MR_i = \gamma_0 + \gamma_1 RV_{1i} + \gamma_2 RV_{2i} + u_I$

RV_1/RV_2	γ_0	t-stat	γ_1	t-stat	γ_2	t-stat	R^2
σ/Σ	−1.00	−2.96	0.02	0.11	0.25	1.07	0.50
β/β^D	−1.01	−2.72	−0.65	−1.30	2.01	4.26	0.58

Panel B: $MR_i = \gamma_0 + \gamma_1 RV_{1i} + \gamma_2 RV_{2i} + \gamma_3 RV_{3i} + \gamma_4 RV_{4i} + u_I$

$RV_1/RV_2/RV_3/RV_4$	γ_0	t-stat	γ_1	t-stat	γ_2	t-stat	γ_3	t-stat	γ_4	t-stat	R^2
$\sigma/\Sigma/\beta/\beta^D$	−0.99	−2.43	−0.02	−0.12	−0.72	−1.13	−0.00	−0.01	2.20	2.33	0.58

MR, mean return; RV, risk variable; σ, standard deviation; β, beta (with respect to the world market); Σ, semideviation; β^D, downside beta (with respect to the world market). Significance based on White's heteroskedasticity consistent covariance matrix. Critical values for a two-sided test at the 5% significance level: 2.06 and 2.07 in panels A and B, respectively.

Table 3
Spreads

	β	MR	β^D	MR
P1	1.48	1.65	1.97	2.15
P2	0.88	1.34	1.36	0.84
P3	0.41	0.51	0.83	0.51
Spread P1–P3	1.07	1.14	1.14	1.63
Annualized spread		14.60		21.48
Relative spread		1.07		1.43

Portfolio 1 (P1) is the riskiest portfolio (largest betas or largest downside betas); portfolio 3 (P3) is the least risky portfolio (lowest betas or lowest downside betas). MR, mean return; β, beta (with respect to the world market); β^D, downside beta (with respect to the world market). 'Relative spread' defined as the ratio between the 'Spread P1–P3' in mean returns and the 'Spread P1–P3' in the risk measure. MR in %.

regression with all four risk variables considered; i.e.

$$MR_i = \gamma_0 + \gamma_1 RV_{1i} + \gamma_2 RV_{2i} + \gamma_3 RV_{3i} + \gamma_4 RV_{4i} + \upsilon_i, \quad (17)$$

where RV_1, RV_2, RV_3, and RV_4 stand for the first, second, third and fourth risk variable of the model, respectively.

As the table shows, when jointly considered, neither the standard deviation nor the semideviation are significant, which is likely to be due to the high correlation between these two explanatory variables (0.98). When beta and the downside beta are jointly considered, on the other hand, only the downside beta comes out significant. Finally, when all four risk variables are jointly considered, again it is only the downside beta that comes out significant.

3.2. Economic significance: spreads in risk and return

In order to check for the robustness of the results discussed in the previous section, I divided all markets into three equally-weighted portfolios ranked by beta, and calculated the spread in mean returns between the riskiest portfolio (the one with the largest betas) and the least risky portfolio (the one with the lowest betas). Then I repeated the process by ranking the markets by downside beta and calculating again the spread between the riskiest portfolio (the one with the largest downside betas) and the least risky portfolio (the one with the lowest downside betas). The relevant results are reported in Table 3.

As the table shows, the average beta of portfolio 1 is over three and a half times larger than the average beta of portfolio 3, and that spread spans a difference in mean monthly returns of 1.14% (14.60% annualized). The average downside beta of portfolio 1, however, is less than two and a half times larger than the average downside beta of portfolio 3, and that spread spans a difference in mean monthly returns of 1.63% (21.48% annualized). In other words, return differences spanned by downside beta are larger than return differences spanned by beta by almost 700 basis points a year.

Furthermore, dividing the spread in monthly mean returns by the spread in the risk measure we obtain the relative spread, which is 1.07 for the portfolios ranked by beta and 1.43 for the portfolios ranked by downside beta. In other words, these relative spreads indicate that mean returns are clearly more sensitive to differences in downside beta than to equal differences in beta.

Finally, a linear interpolation indicates that the beta of portfolio 3 would have to be 5.2 times larger than the beta of portfolio 1 in order to span the same spread in returns spanned by the downside beta of portfolio 3 being 2.4 times larger than the downside beta of portfolio 1.[3] Put shortly, returns in EMs are *much* more sensitive to downside beta than to beta.[4]

3.3. Required returns on equity: the CAPM vs. the D-CAPM

A brief recap is in order at this point. The results reported and discussed so far indicate that (1) all four risk variables considered are significantly related to returns in EMs; (2) the downside beta is the variable that best explains the cross-section of returns ($R^2 = 0.55$); (3) when beta and downside beta are jointly considered, only the downside beta comes out significant; (4) when all four risk variables are jointly considered, only the downside beta comes out significant; and (5) returns are much more sensitive to differences in downside beta than to equal differences in beta.

I turn now to compare the required returns on equity generated by the CAPM, based on beta and given by Eq. (5), and the D-CAPM, based on the downside beta and given by Eq. (11). In both cases, a risk-free rate of 5.03% and a market risk premium of 5.5% are used.[5] The estimates for all markets in the sample are reported in Table 4.

Note, first, that the average downside beta is 50% larger than the average beta; i.e. EMs exhibit more relative downside volatility than relative volatility. Note, also, that the average required return on equity generated by the D-CAPM (12.65%) is over 250 basis points higher than the average required return on equity generated by the CAPM (10.11%). Finally, note that in some markets such as Argentina and Turkey the difference in the cost of equity generated by the CAPM and the D-CAPM is very significant: Almost 600 basis points a year in the case of Turkey and over 640 basis points a year in the case of Argentina. In fact, for about one

[3] Note that the average beta of portfolio 1 is 3.61 times larger than the average beta of portfolio 3, and that an increase in beta by a factor of 3.61 spans a spread in returns of 1.14% a month. Hence, in order to span a spread in returns of 1.63% a month, betas would have to increase by a factor of 5.2 ($= 3.61 \times 1.63/1.14$).

[4] Although returns are also much more sensitive to downside beta than to beta in developed markets, the difference is less meaningful from an economic point of view. When developed markets are ranked by beta, the annualized spread between the riskiest and the least risky portfolio is 0.70%; when developed markets are ranked by downside beta, the annualized spread is 1.77%. The relative spreads when developed markets are ranked by beta and downside beta are 0.13 and 0.34, respectively. See Estrada (2002c).

[5] The 5.03% risk-free rate is the yield on 10-year US Treasury Notes on Dec/31/2001. The 5.5% market risk premium is similar to that used by Stulz (1995).

Table 4
Required returns on equity. CAPM vs. D-CAPM

Market	β	β^D	CAPM	D-CAPM	Difference
Argentina	0.66	1.82	8.64	15.06	6.42
Brazil	1.44	2.16	12.96	16.92	3.95
Chile	0.57	0.95	8.18	10.25	2.08
China	1.13	1.39	11.24	12.67	1.43
Colombia	0.32	0.81	6.80	9.49	2.69
Czech Rep.	0.66	1.29	8.68	12.15	3.47
Egypt	0.53	0.90	7.93	9.98	2.05
Hungary	1.53	1.91	13.42	15.52	2.10
India	0.54	1.10	8.02	11.06	3.04
Indonesia	0.97	1.60	10.37	13.85	3.48
Israel	0.63	0.87	8.49	9.82	1.33
Jordan	0.11	0.32	5.66	6.77	1.11
Korea	1.25	1.34	11.89	12.42	0.53
Malaysia	1.02	1.33	10.65	12.34	1.69
Mexico	1.12	1.47	11.21	13.12	1.91
Morocco	−0.12	0.39	4.38	7.18	2.80
Pakistan	0.49	1.00	7.74	10.54	2.80
Peru	0.74	1.19	9.12	11.60	2.47
Philippines	1.10	1.40	11.06	12.73	1.67
Poland	1.66	2.02	14.16	16.12	1.97
Russia	2.69	2.85	19.82	20.69	0.87
South Africa	1.10	1.33	11.10	12.34	1.24
Sri Lanka	0.61	1.11	8.37	11.14	2.76
Taiwan	0.87	1.49	9.79	13.25	3.46
Thailand	1.41	1.75	12.79	14.64	1.85
Turkey	1.04	2.13	10.77	16.74	5.97
Venezuela	0.85	1.46	9.69	13.07	3.38
Average	0.92	1.38	10.11	12.65	2.54

β, beta (with respect to the world market); β^D, downside beta (with respect to the world market). Required returns on equity for the CAPM and the D-CAPM follow from Eqs. (5) and (11), respectively, a risk-free rate of 5.03%, and a market risk premium of 5.5%. All numbers other than β and β^D in %. Annual figures.

third of the markets in the sample such difference is at least 300 basis points a year. In other words, it does make a significant difference whether the expected cash flows of projects or companies are discounted at rates based on the CAPM or on the D-CAPM. These differential returns are simply too large for practitioners to ignore.

3.4. A Final digression: why does the downside beta work?

The superiority of the downside beta over beta in explaining the cross section of stock returns in EMs may be a somewhat surprising finding to some. In this final section, I briefly attempt to justify the plausibility of this empirical result.

First, as mentioned above, it is rather obvious that investors do not dislike volatility per se; they only dislike downside volatility. Investors do not get away from stocks that exhibit large and frequent jumps above the mean; they get away from stocks that exhibit large and frequent jumps below the mean. Investors are not afraid of obtaining more than their minimum acceptable return (MAR); they are afraid of obtaining less than their MAR.

Second, aversion to the downside is consistent with both the theory and findings in the literature of behavioral finance. It is clearly consistent, for example, with the S-shaped utility function of prospect theory pioneered by Kahneman and Tversky (1979), in which losses of a given magnitude loom larger than gains of the same magnitude. In this framework, utility is determined by gains and losses with respect to the status quo rather than by wealth.

Finally, the superiority of downside beta may be related to the contagion effect in financial markets.[6] Note that in the traditional MVB framework, the appropriate measure of risk is beta when markets are integrated, and the standard deviation when markets are segmented. The superiority of the downside beta may then be explained by the fact that markets are more integrated on the downside than on the upside due to the contagion effect, something that most data seem to suggest.

4. Concluding remarks

Beta and the CAPM (and the behavioral model from which they follow, MVB) have been both widely used but also widely debated for over 30 years. Most of the arguments against beta have been by and large empirical, focusing on whether beta explains the cross-section of stock returns. Between my previous articles (Estrada, 2002b,c) and this article, I have questioned beta and the CAPM from both a theoretical point of view (by showing that MSB is at least as plausible as MVB) and an empirical point of view (by showing that the data supports the downside beta over beta).

In this article, I have made a parallel between the standard framework based on MVB, the CAPM, and beta, and an alternative framework based on downside risk; i.e. on MSB, the D-CAPM, and the downside beta. I have also shown the appropriate way to estimate the downside beta, the measure of risk proposed in this article, and how to integrate it into an alternative pricing model, the D-CAPM, proposed in this article to replace the CAPM.

The evidence discussed supports the downside risk measures over the standard risk measures, and particularly the downside beta, which explains almost 55% of the variability in the cross-section of returns in EMs. The evidence also shows that returns in EMs are much more sensitive to differences in downside beta than to equal differences in beta. Furthermore, the D-CAPM generates average required returns on equity over 2.5% a year higher than those generated by the CAPM, a substantial difference that can make or break many investment projects and affect significantly the valuation of companies. As argued above, this difference is simply too large for practitioners to ignore or even take lightly.

Finally, the D-CAPM has an advantage over three-factor models in that it is easier to implement; in fact, it is just as easy to implement as the CAPM. Therefore,

[6] I would like to thank Mark Kritzman for suggesting this idea to me.

this article questions the standard framework based on MVB, the CAPM, and beta, and proposes to replace it with an alternative framework based on MSB, the D-CAPM, and the downside beta. And the empirical evidence reported and discussed supports this proposal.

Acknowledgments

This article was specially prepared for the 'Valuation in Emerging Markets' conference (Darden, University of Virginia), May 29–31, 2002, and is a reduced version of my article 'Mean–Semivariance Behavior (II): The D-CAPM.' For valuable comments and discussions on the extended article and this reduced version I would like to thank Tom Berglund, Bob Bruner, Manolo Campa, Cam Harvey, Mark Kritzman, Andy Naranjo, Luis Pereiro, Ana Paula Serra, Clas Wihlborg, seminar participants at Darden and Faculdade de Economia do Porto, and participants at the 'Valuation in Emerging Markets' conference, the 2002 FMA meetings (Copenhagen, Denmark) and the 2002 EFMA meetings (London, UK). Alfred Prada provided valuable research assistance. The views expressed below and any errors that may remain are entirely my own.

Appendix A:

Table A1
Summary statistics (monthly stock returns)

Market	MR	σ	ρ	β	Σ	Θ	β^D	SSkw	Start
Argentina	2.96	18.19	0.15	0.66	10.17	0.56	1.82	10.78	Jan/88
Brazil	2.91	17.37	0.35	1.44	11.55	0.58	2.16	2.51	Jan/88
Chile	1.74	7.56	0.32	0.57	5.27	0.56	0.95	−0.42	Jan/88
China	−0.72	12.72	0.37	1.13	7.92	0.54	1.39	4.27	Jan/93
Colombia	0.29	9.68	0.14	0.32	6.55	0.38	0.81	1.41	Jan/93
Czech Rep.	0.24	9.28	0.30	0.66	6.59	0.69	1.29	0.23	Jan/95
Egypt	0.46	8.69	0.25	0.53	5.18	0.61	0.90	4.94	Jan/95
Hungary	1.68	11.84	0.54	1.53	8.17	0.82	1.91	0.94	Jan/95
India	0.42	8.88	0.26	0.54	6.04	0.56	1.10	1.09	Jan/93
Indonesia	1.26	17.08	0.24	0.97	9.88	0.50	1.60	10.38	Jan/88
Israel	0.76	7.13	0.37	0.63	5.42	0.49	0.87	−2.01	Jan/93
Jordan	0.16	4.45	0.11	0.11	3.11	0.32	0.32	−0.80	Jan/88
Korea	0.93	12.56	0.41	1.25	7.68	0.54	1.34	6.83	Jan/88
Malaysia	0.95	10.09	0.42	1.02	6.87	0.60	1.33	3.16	Jan/88
Mexico	2.40	10.41	0.45	1.12	7.67	0.60	1.47	−2.23	Jan/88
Morocco	0.70	4.95	−0.10	−0.12	3.35	0.41	0.39	1.62	Jan/93
Pakistan	−0.02	12.08	0.17	0.49	7.91	0.39	1.00	1.96	Jan/93
Peru	0.97	9.47	0.33	0.74	6.55	0.56	1.19	0.76	Jan/93
Philippines	0.71	10.36	0.44	1.10	6.94	0.63	1.40	2.78	Jan/88
Poland	2.59	17.86	0.39	1.66	10.03	0.62	2.02	11.00	Jan/93
Russia	3.59	22.22	0.50	2.69	15.27	0.65	2.85	0.56	Jan/95
South Africa	0.78	8.20	0.56	1.10	6.02	0.68	1.33	−1.90	Jan/93
Sri Lanka	0.10	10.44	0.24	0.61	6.67	0.51	1.11	4.16	Jan/93
Taiwan	1.27	12.47	0.29	0.87	8.19	0.57	1.49	2.44	Jan/88
Thailand	0.72	12.73	0.46	1.41	8.80	0.62	1.75	1.25	Jan/88
Turkey	2.34	18.90	0.23	1.04	11.86	0.56	2.13	4.47	Jan/88
Venezuela	1.33	14.65	0.24	0.85	10.18	0.44	1.46	−0.23	Jan/93
Average	1.17	11.86	0.31	0.92	7.77	0.55	1.38	NMF	N/A
World	0.78	4.17	1.00	1.00	3.11	1.00	1.00	−2.14	Jan/88

MR, mean return; σ, standard deviation; ρ, correlation (with respect to the world market); β, beta (with respect to the world market); Σ, semideviation; Θ, downside correlation (with respect to the world market); β^D, downside beta (with respect to the world market); SSkw, coefficient of standardized skewness. MR, σ, and Σ in %. All data through Dec/2001.

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