XVII SEMEAD
Seminários em Administração

outubro de 2014
ISSN 2177-3866

Relationship between downside risk measures and return in the Brazilian market

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Research Field: Finance

TITLE: RELATIONSHIP BETWEEN DOWNSIDE RISK MEASURES AND RETURN IN THE BRAZILIAN MARKET

Abstract

Recent research shows that distortions of distributional properties of emerging markets returns may impact the effectiveness of conventional asset pricing models. Last years a mean-semivariance framework has been proposed as an alternative approach to portfolio analysis since different investors assign a lower weight to positive deviations from the mean than to negative ones. The present work aims to investigate empirically the relationship between risk and return in a downside risk framework and in a regular risk framework by utilizing daily returns of securities trades on the Sao Paulo Stock Exchange. Using individual equities from Brazilian market we separately examine conditional returns in upturn and downturn periods in order to indentify the potential contribution of downside risk measures to explain asset pricing in both states of economy. The results reveal that for downturn periods, downside risk measures are better in explaining risk returns than the regular risk measures. The paper also concludes that both co-skewness and downside beta are priced by investors, and they may capture different aspects of downside risk.

Keywords: Asset Pricing, Downside risk, Downside Beta, Co-skewness.

1. Introduction

The cost of capital is one of the most important factors to assess any project or company. For an investor point of view, it represents the lowest required return to provide and allocate resources at the firm. Thus, this cost of equity should be equal to the expected rate of return on alternative investments with similar risk characteristics within the capital market.

One of the main problems of addressing investment portfolio management in emerging capital markets is to quantify expected return and risk, and also how to assess accurately the risk-return relationship. The Capital Asset Pricing Model (CAPM) (Sharpe, 1965; Lintner, 1966 & Black, 1972) like others market equilibrium models of capital assets pricing, tries to capture the relationship between the systematic risk of an asset, measured as the equity´s beta, and the expected rate of return on that asset. The most common application of the CAPM is to estimate the expected return to equity, which is used among others, for pricing financial assets and business valuation, capital budgeting and portfolios performance simulations.

There exists a lot of empirical evidence that the traditional model of CAPM has some flaws and does not capture all risk factors. Despite CAPM has been widely and strongly criticized during the last 40 years, most practitioners and analysts continue using the traditional CAPM construction. Accordingly to Graham & Harvey (2009) and Brounen et. al (2004), 75% of US CFO´s and 45% in Europe use CAPM to assess cost of capital. This widely utilization is based on its simplicity in a low cost and relative high effectiveness process, keeping CAPM more popular among analysts than both arbitrage and multi-factor models.

The CAPM assumes a normal distribution of returns, and the model´s underlying assumption is that the perception of risk is attributed by the dispersion on both sides of the mean. Estrada (2000, 2002) criticized the use of variance and therefore also the standard deviation as a measure of risk and he proposed to measure it by the semi-standard deviation of the distribution. He argued that the variance is a good measure of risk only when return's distribution is both symmetrical and normal and he points out that empirical evidence contradicts these both underlying requirements. Estrada (2000) highlights three pros in using semi-variance as a measure of risk: a) it captures the preference of investors upside risk b) is more useful than variance when distribution is asymmetric c) semi-variance gives the same information than variance and skewness and therefore is more efficient for use in asset pricing. Ang et al. (2006) tested cross sectional asset pricing and demonstrated that investors are willing to incorporate a premium for downside risk. The rationale behind this theory is that measures that incorporate only the semi-standard deviation are more useful when dealing with asymmetric distributions as these factors are more sensible capturing the volatility that affects downside returns. From an investor point of view, this is could be explained by saying that investors are mainly interested in the risk of losses rather in the "risk" of gains (represented the latter by the right side of the normal distribution curve). This investor´s concern about the preference for positive skewness of asset returns has been already addressed by the literature, deriving in some interesting researches about higher moment's behaviors. The evidence shows that the risk premium of assets will depend on their co-skewness, with investors preferring assets with positive co-skewness (Huan & Litzenberger, 1988).

2. Review of Empirical Literature

The CAPM, attributed to Sharpe (1965); Lintner (1966) & Black (1972), is based on Markowitz´ modern portfolio theory of Markowitz (1952), involving that the risk and return of investments are effectively measured by variance and mean of the expected return from the investment. Throughout this concept CAPM arrives to the conclusion that on efficient portfolios there exist a linear risk-return relationship represented by the Capital Market Line (CML).

From the early seventies vast empirical evidence reinforced CAPM as a robust model. The most significant research in this area was conducted by Black, Jensen and Scholes (1972). They tested CAPM since 1926 to 1966 using NYSE market data and examining whether intercepts comes to zero on market beta for cross sectional and time series regressions of excess return. They found positive relationship between market beta and expected return. In other relevant studies, Hamada (1972) found linkage between systematic risk and leverage and Fama & MacBeth (1973) provided evidence that linear relationship between the average return and beta still holds even when data covers a long time period.

Markowitz (1952,1959), who initially proposed the mean variance framework on the development of modern portfolio theory, suggested in his seminal work the use of semi-variance as better measure of risk. Due to lack of resources at that time, Markowitz (1959) stays with the mean variance measure meaning that deviation both below and above mean equally contribute towards the risk perceived by investors. In the very beginning of the model Roy (1952), argues that investor cares from disaster and his main concern is to avoid it, in other words, he holds the theory of the "safety-first rule". Lybby & Fishburn (1977), support this theory, suggesting that investors are more concerned with deviation of returns below the mean. Gul (1991), who develop rational Disappointment Aversion (DA) utility function, points out that investors display a larger aversion to losses relative to the attraction for gains. Hence investor seems to be loss averse, not risk averse.

Hogan & Warren (1974), and later Bawa & Lindenberg (1977), developed an asset pricing model based on expected return semi-variance, presenting the return of the security as a linear function of its downside beta computed with respect to the market portfolio.

Price et al. (1982) tested returns on the US stock over a sample period from 1927 to 1968 and found that the semi-variance risk estimators of risk differ from the variance based risk measures. Furthermore, they suggested that measuring risk using the standard CAPM (mean variance approach) leads to overestimate the risk of high beta stocks and underestimate the risk of low beta stocks. Due to these findings and the hypothesis of borrowing and lending at the risk free rate, it would be expected that return and downside risk share positive and linear relationship, meaning that downside risk beta is a complete measure of risk.

Harlow & Rao (1989) provided evidence that the Mean Semi-variance CAPM seems to capture better the cross-section of stock returns than the Mean Variance- CAPM. They found a measure of downside risk, named the generalized mean lower partial moment (MLPM), based on downside deviations below the mean of returns of an asset *i* and the market portfolio. Thus, this brings a sensibility measure of the security´s returns (below and above average returns) to changes in market returns below mean.

Ang et al. (2001) analyze daily US stock data from 1964 to 1999 and within DCAPM framework shed some light to explain momentum effect. Additionally, Ang et al. (2006) provide a detailed empirical examination of the explanatory power of downside beta for individual shares in the US market. They showed that the shares which co-vary strongly with the market during market downturns do have higher average returns, reporting a 6% risk premium for downside risk.

The case in emerging markets merits separate examination, as there is vast evidence that asset returns exhibit very high volatility and are not normally distributed. Beakert & Harvey (1997) indentified significant skeweness and kurtosis in emerging market returns, with persistence of skewness over time.

3. Background theory and research question.

As explained before, the underlying fundamentals behind the development of downside CAPM models in emerging markets is that CAPM baseline requirements, concerning distributional properties of symmetry and normality of expected stock returns, are not achieved, thus investors should be clearly rewarded for exposure to downside risk measures.

3.1 Downside Beta

A notable contribution within the issue of downside risk in emerging markets came from Estrada (2000). Estrada (2000) and later Pereiro (2006), suggested to use the downside beta (β-), a sensitivity measure defined as the ratio between the semi-deviation of returns with respect to the mean in market i and the semi-deviation of returns with respect to the mean in the world market. This measure of risk is empirically supported as it explained the variations in the cross section of stock returns in emerging markets. Estrada (2002) uses market indices to provide evidence on the explanatory power of downside beta. Using a coefficient that results from the comparison of securities returns and market portfolio returns, when each variable is below their respective means, the conventional beta coefficient is not as good to explain the returns of individual assets as the downside beta. In other words, Estrada (2002) shows that mean returns are more sensitive to changes in downside beta than to equal changes in conventional beta. Using this approach, Pereiro (2006) found some empirical explanatory power in DCAPM for Argentinean market. With all this emerging markets evidence for non normality and investor´s preference for downside risk, DCAPM seems to be a good substitute to CAPM, (and therefore downside beta a great alternate to conventional beta), both for theoretical and empirical grounds.

3.2 Co-skewness

If stock prices exhibit non normality properties, then the importance of skewness cannot be overlooked. Kraus & Litzenberger (1976) extend the CAPM to incorporate the effect of skewness in asset pricing. They show that investors, with decreasing marginal utility of wealth and non-increasing absolute risk aversion, prefer positive skewness portfolios (more right skewed). Hence, assets that decrease a portfolio’s skewness (i.e., that make the portfolio returns more left skewed) are less desirable and should command higher expected returns. Similarly, assets that increase a portfolio’s skewness should have lower expected returns (Harvey & Siddique, 2000).This suggests that investors value higher moments and this fact leads us into the study of the third and fourth moments to explain better the results in future markets. Ang & Chua (1979) demonstrated that ignoring the third moment would generate a bias in performance evaluation. To date, most emphasis has been placed on the impact on co-skewness on asset prices, rather than skewness, to reflect the argument that investors are not compensated for diversifiable skewness in equilibrium (Ingersoll, 1975) and recent research deal with this higher co-moment measure. Kraus & Litzenberger (1976) early introduce the definition of co-skewness of an asset. They stated that the co-skewness of a security represents the marginal contribution of the security to the skewness of a broader portfolio. According Harvey & Siddique (2000), a negative co-skewness measure means that, when incorporated into a portfolio, the security is adding negative skewness, and investors dislike this fact because their results yield an amplified high average stock returns for low co-skewness stocks, fact that increases the probability of obtaining undesirable extreme values.

3.3 Research question

Downside beta is not to be mixed up with co-skewness in the sense that the downside market movements should be captured by downside beta in a conditional and inter-temporal manner, while co-skewness should not show any changes for asymmetrical properties for down and up markets even though co-skewness may vary over time. However according to the literature, co-skewness may capture some aspects of downside covariation that are not included in downside beta premium, so we believe that co-skewness and downside beta should capture different aspects of downside risk. As a matter of fact, Galagedera & Brooks (2007) include downside co-skewness to downside beta to asses and compare the performance of downside risk with and without co-skewness. They conclude that co-skewness has to be included in a complementary way to the downside risk premiums.

The purpose of this paper is to test both downside beta and co-skewness in a downside framework approach for the Brazilian equity market and therefore to examine the linkage between the risk/reward relationships between these two measures and others systematic measures of risk.

We believe that the main advantage of using downside beta for the Brazilian market relies on the fact that it does not require compliance with the symmetry and normality of the distribution, uncommon properties in emerging markets. Moreover, Brazilian investor should really be concerned of negative volatility of returns.

In the other side, the main benefit of using co-skewness is that the asset pricing models, when supported by higher moments, allow researchers to focus on investor preferences over particular features of the underlying stock return distribution (Dittmar, 2002; Kraus & Litzenberger, 1976)

In his paper we aim to test if investors of Brazilian market are rewarded for exposure to both co-skewness and downside beta. As we showed before, to date existing asset pricing literature points out the convenience of using these both downside risk measures in which investors are compensated for holding, in a semi–variance environment, systematic and co-skewness risk. Therefore, the major contribution of this paper is to provide empirical evidence about the role of downside beta and co-skewness in Brazilian market securities returns.

Regarding this asset pricing issue in Emerging Markets and specifically focusing in the Brazilian case, we decided to state the following main research question:

Would the analysis of systematic downside deviation help to receive a more adequate relation between market risk and return in Brazil?

4. The Data

The research will be based on daytime data of exchange auctions of financial assets that compound around the 85% of the capitalization of the Brazilian market index Ibovespa. The source of the daily returns is provided by Economatica database. The Ibovespa Index is a gross total return index weighted by traded volume and is comprised of the most liquid stocks traded on the Sao Paulo Stock Exchange. It is the most widely used index in the Brazilian equity market and it is composed of 66 stocks (BMF BOVESPA, 2013). An obvious concern is that, since there are large numbers of small thinly traded shares in the Brazilian Market, an accurate estimation of their risk attributes will not be possible. Although there are 66 stocks comprising the index, we limit our investigation only to the most representative ones in terms of market capitalization. A further selection criterion is employed as some emerging market companies may suffer a lack of liquidity (Feldman & Kumar, 1995). For all shares we estimate the proportion of days with zero returns, and we exclude those shares recording a proportion of zero daily returns above 50%. These selection criteria result in a substantial reduction of the sample that remains in 49 stocks.

The study covers the period from June 1st 2006 to July 3th 2013, which means a window of 1849 observations per share. As will be explained later, for estimating purposes and better forecasting explanatory power we divide this entire period in some sub periods because the model should test both upturn and downturn market periods.

5. Methodology

Our research proposal is to test both the viability and strength of Coskewness and Downside Beta when estimating expected returns for Brazilian Market Stocks. Due to the continuous nature of information and compounded return rates, in order to calculate the daily return of the stocks we use the following equation:

$$r = \ln \frac{P(t)}{P(t-1)} \qquad \textbf{(1)}$$

With all the data we form two sub-samples, one containing company returns during one semester periods of downturn and one for those semesters of upturns. A downturn period is defined as a semester in which overall market returns are below the market risk free rate. For this analysis, this market excess return is calculated by the nominal IBOVESPA return “rm” minus the nominal daily inter-bank CD rate “rf“(compounded monthly). A semester in which market returns exceed their risk-free rates is designated as an upturn period. An examination of our data indicates that approximately 57 % of all periods are upturns and 43% are downturns.

The present study considers four risk measures. Co-skewness of returns is our primary measure of downside risk. Harvey (1995) defines co-skewness as the component of an asset´s skewness related to the market porfolio´s skewness. Using individual share data, Harvey & Siddique (2000) find that co-skewness has explanatory power for share returns, after allowing for other established explanatory factors. Our empirical estimator for co-skewness is as follows:

$$Cskw = \frac{\frac{1}{N-1}\sum_{t=1}^{N}(r_{it}-\bar{r})(r_{mt}-\bar{r}_m)^2}{\sqrt{\frac{\sum_{t-1}^{N}(r_{it}-\bar{r})^2}{N-1}}\frac{\sum_{t-1}^{N}(r_{mt}-\bar{r}_m)^2}{N-1}} \qquad \textbf{(2)}$$

In all cases r_{it} is daily return on share I and $\bar{r}$ is average return. Ibovespa index returns are indicated by *m*, so that r_{mt} is its daily return and $\bar{r}_m$ is average market return. For comparison purposes we also consider two related idiosyncratic measures of risk, the skewness (*Skew*) of returns, and the variance of returns (*Var*). Our empirical estimator for skewness of returns is the adjusted Fisher-Pearson standardized moment coefficient:

$$Skew = \frac{N}{(N-1)(N-2)} \frac{\sum_{t=1}^{N}(r_{it}-\bar{r})^3}{\sqrt{\frac{\sum_{t=1}^{N}(r_{it}-\bar{r})^2}{N-1}}} \qquad \textbf{(3)}$$

The estimator for volatility is the variance of returns, calculated as:

$$Var = \frac{\sum_{t=1}^{N}(r_{it}-\bar{r})^2}{N-1} \qquad \textbf{(4)}$$

Downside beta (β^-) is a further indicator of downside risk. Ang et al. (2006a) provide a detailed empirical examination of the explanatory power of downside beta for individual shares in the US market. We could define downside beta (β^-) as an indicator of negative sensibility to market risk and it should be computed when the market return is below the risk free rate (Petengill et al. 1995). Therefore, downside beta measures the covariance between stock and market returns in relation to the variance of the market when the market is below the risk free rate. The estimator is:

$$\beta^{-} = \frac{Cov(r_i, r_m | r_m < r_f)}{Var(r_m | r_m < r_f)} \qquad \textbf{(5)}$$

For reason of completeness, upside betas (β^{+}) are included too. These are calculated when the market return is above the risk free rate. Beta (β) is computed in the conventional way, by calculating the security market line of each company.

6. Results and Implications

Firstly, we test normality of daily returns for each company. We use the software SPSS® and Komolgorov-Smirnov testing method to test the sample that has 783 inputs for upturn periods, 1066 for downturn periods, and 1849 for all periods combined. Results are shown in table 1. We also expose in this table the complete sample of companies and risk measures excepting betas.

As shown in Table 1 neither any company return's distribution nor IBOVESPA index distribution seems to be normal, as the null hypothesis of the Komolgorov-Smirnov normality test is rejected within a statistical confidence level of 99%. The implication of this result means that if any financial practitioners tempt to use conventional CAPM for the Brazilian market to asses prices, it could be some bias in the final outputs since normality is an assumption for CAPM.

This first result leads us into further analysis. In this section we aim to evaluate if downside risk measures could be important in explaining stocks returns. If there is a cross-sectional relationship between returns and these measures, we expect to find patterns between them. For that purpose we perform the tests based on equally weighted portfolios and the results are presented in Tables 2 to 5. For each analysis we mention the expected result based on existing literature and then we compare it with our result. Estimates for all companies are ranked in quintiles for the whole period and companies are then allocated to five portfolios. For Table 2 to 5, average skewness of firms allocated to each portfolio is recorded in the column headed "Skew", and average daily return is reported in the column headed "Return". Average portfolio values of variance (Var) and co-skewness (Cskw) are also recorded. We also show differences between highest and lowest ranked portfolios, and then t-test is performed to confirm the presence of a significant difference in returns. A first ranking presents results for the entire period of study (designated All Periods). A second ranking only considers upturn years (designated Upturn Periods), whereas a final ranking (designated Downturn Periods) assesses returns in downturn years. We also test for significant differences between our defined measures of risk (r, skew, cskw, var) in upturns, and in downturns. Worth noting that T-test for equality of means could only be performed if normal distribution for each portfolio is confirmed. Given that each portfolio is composed by less than 30 companies, we use Shapiro-Wilk test to confirm normality of each sample portfolio´s returns. This procedure is repeated for Tables 2, 3, 4 and 5.

In Table 2 we consider skewness of returns since the literature review spotlights it as a potential risk measure for emerging markets. Therefore, this Table aims to find some relationship between skewness and returns. We expect over all periods a preference for positive skewness that causes investors to accept lower returns, therefore we expect a negative relationship between skewness and returns. We also have no expectation that skewness of returns will have a particular linkage to market upturns or downturns. However, our findings are contrary to ours expectations since Table 2 shows a positive relationship between skewness and returns. We also find significant differences between returns in the highest and lowest ranked portfolios. Firms offering strong positively performances have positively skewed returns, and on the other hand, firms with poorest returns show negative skewnees. We note the same significant positive relationship between skewness and returns for both upturn and downturn periods. The significance of performed t-statistics indicates that skewness in not particularly associated with either downturns or upturns.

In Table 3, we assess the explanatory power of variance in the Brazilian market. Exposure to volatility is unattractive to investors, so we expect that if an investor assumes to own a portfolio that exhibit high levels of variance he will required higher return. According to the literature, variance is likely to be associated with both upturns and downturns, so we shouldn't expect a specific separate relationship in either period.

When focusing on "all periods" at Table 3, we can´t find any relationship between variances and returns, initially suggesting little evidence of a relationship between volatility and performance, but if we concentrate on separate downturn and upturn periods, we note that for upturn periods, high variance portfolios tend to offer superior performances and for downturn periods high variance portfolios tend to suffer greater losses. Although neither relationship is monotonic, significant differences between highest and lowest ranked portfolios are confirmed for both upturn and downturn periods. These findings for both separate periods (bullish and bearish market) are aligned with our previous expectations because it means that exposure to volatility (high variance) is rewarded with excess returns during upturns, and is penalized with losses during downturns.

We also note that for Tables 2 and 3, regardless the period, variance appear to be related to skewness: shares in the high variance portfolios exhibit positive skewness and viceversa. Skewness appears to possess systematic relation to expected returns and variance, meaning that any relationship between returns and skewness may be partly explained by variance. This conclusion is aligned with Harvey & Siddique (2000), since they found significant impact of skewness on estimated conditional volatility.

In Table 4, we consider co-skewness of returns, as we want to test the downside risk effectiveness of this measure. Co-skewness may capture some aspects of an investor risk exposure; thereby we expect to see this effect clearly in downturn periods. Co-skewness represents the contribution of individual shares to the skewnesss of a broader portfolio. As defined in equation (2), co-skewness is determined by the covariance of share returns with market return, which is a higher momentum indicator of market volatility. We expect higher volatility during downturns and if we have a consistent outcome, negative co-skewness will be associated with relatively lower returns. If volatility is indeed more commonly associated with downturns, different kinds of relationships or/and levels of significance may be identified in upturn and downturn markets. In Table 4 portfolios are ranking by estimates of co-skewness. When we concentrate on separate upturn and downturn periods, we could note that low co-skewness portfolios tend to offer poorer performance in both periods, although we find that only for downturn periods the results are statistically significant. These findings mean that for upturn periods the effect of co-skewness seems not be statistically relevant in stocks returns and therefore we cannot validate any relationship when the economy in Brazilian market is growing. Otherwise, during downturns, t-test indicates significant differences for returns and co-skewness between highest and lowest co-skewness ranked portfolios and there exist a positive monotonic relationship. This result confirms that losses may be probable from negative (lower) co-skewness during downturns. Indeed, results in table 4 suggest that lower (more negative) returns have a greater volatility during downturns, and this effect may be relevant due to association of volatility with downturns. Hence investors in Brazil should be aware that holding a portfolio with negative co-skewness could lead to greater losses during downturn periods and these losses may not be rewarded with good performance during upturns.

In table 5, portfolios are formed using ranking estimates on betas. According to conventional CAPM theory, beta should have a positive relationship with share returns, however Pettengill et al. (1995) states that positive relation may only exist during market upturns. A negative relationship is expected during turndowns, as stocks with greater exposure will offer worse results. The overall relationship in both downturn and upturn periods combined, named as "all periods", will depend on the weight of the beta effect on each period. In a growing economy upturn periods are more likely, so we should expect a positive relationship. In our case of study, we have slightly more upturns periods (57% up vs. 43% down), then we should have a positive relationship, but for obvious reasons the effect may be very weak to be significant. Downside beta is conditioning on observations when market performance is below free risk rate. This risk exposure is also unattractive for investors, because during downturns, investor accepting higher downside betas should suffer greater losses. Therefore we expect a negative relationship between downside beta and returns. Otherwise, upside beta is conditioning on observations when market performance is above the risk free rate. Greater beta shares should perform well, so a positive relationship between upside beta and returns is expected. Another forecast to be tested is the relationship between downside beta and co-skewness. Although both are downside measures of risk, both are differently constructed and therefore they may capture different features of investor's downside risk exposure.

For overall periods we calculated the conventional beta measure; for downturn periods, we show β^- as explained in equation 5, and for upturns we exhibit upside betas (β^+). We report average portfolio values for beta, and we exclude average skewness values. We again need to concentrate for upturns and downturns periods, as we cannot find a clearly relationship for beta and returns in "all periods together". This may simply mean that the conventional CAPM may not be applicable in the Brazilian market for returns prediction. According to our expectations, exposure to upside beta is rewarded with excess return during upturns although we cannot validate a statistical significance for returns differences between portfolio 1 and 5. Otherwise, exposure to downside beta is penalized with losses during turndowns, this relationship between returns and downside beta is validated with a 10% level significance for returns and 1% level significance for β^- .

Below, in Table 6, we exhibit the results of t-statistics for equality of means between upturns and downturns; the null hypothesis of this test states that beta's mean for both periods is equal. The Pvalue is 0,104 and therefore the null hypothesis cannot be rejected. Anyway, we must take into account, the proximity of Pvalue to 10 %, meaning that we cannot simply assume that the means are equal without studying deeply the whole scenario.

Referring again to Table 5 we also note that it cannot be observed any relationship between downside beta and co-skewness. That could mean that any losses for exposure to negative coskewness may not be related to losses for exposure to downside beta.

7. Conclusions

This paper uses returns of securities traded on the Sao Paulo Stock Exchange (SPSE) and empirically investigates the relationship between risk and return in a downside risk framework and in a regular risk framework. We aimed to test the behavior of two variables related with the expected returns in a semi-variance environment (co-skewness and downside beta).

After testing normality with Komolgorov-Smirnov test, it can be seen that for Brazilian market, normal distribution of returns is not achieved for any security at all. Summarizing the results, it can be observed some strong evidence that there exists a relationship between downside risk measures and returns to portfolios in Brazilian market. Thus, we found that for equally weighted portfolios, the downside risk measures are better in explaining mean returns than variance, skewness and conventional beta. During upturn markets, we cannot conclude about the superiority of the downside risk measures since, even after showing tendencies of direct relationship with returns, t-tests don´t show statistical significance in difference of means between returns for high and low ranked portfolios. Otherwise, for downturn markets, results reveal that both downside beta and co-skewness are priced in downfalls for equity markets. These results are perfectly aligned with Harvey & Sidiqque (2000) and Estrada (2002) since the latter showed that downside beta is more sensitive than conventional beta during downturns and the former demonstrated the importance of the inclusion of co-skewness in the asset pricing platform to help in explaining the variation of equity returns.

Our most interesting finding is that co-skewness seems to possess more interesting features than downside beta from a Brazilian investor point of view, since negative co-skewness is related to greater losses during turndowns and these losses would not be rewarded by greater earnings during upturns. Therefore, an investor would be willing to avoid Brazilian stocks with negative co-skewness of returns within their portfolios. This result is consistent, among others, with Huan & Litzenberger (1988) and Harvey & Siddique (2002), since both papers demonstrated that investors should dislike adding stocks with negative co-skewness into their portfolios, because these stocks would make the portfolio returns more left skewed and finance literature recognize the investor´s preference for positive skewness.

Finally, we found that in downfalls both measures of downside risk (co-skewness and downside beta) independently seem to capture different aspects of downside risk, because both have explanatory power over returns, but they don’t show any direct relationship between each other.

References

Ang, A., Chen, J. and Xing, Y. (2001). Downside Risk and the Momentum Effect. Working Paper 8643, *National Bureau of Economic Research, Massachusetts.*

Ang, A., Chen, J., Xing, Y., (2006). Downside risk. *The Review of Financial Studies 19, 1191–1239.*

Ang, J.S., Chua, J.H., (1979). Composite measures for the evaluation of investment performance. *Journal of Financial and Quantitative Analysis 14, 361–384.*

Bawa, V. and Lindenberg, E. (1977). Capital Market Equilibrium in a Mean-Lower Partial Moment Framework. *Journal of Financial Economics, 5(2), 189-200.*

Banz, Rolf W. (1981), The Relationship between Return and Market Value of Common Stocks. *Journal of Financial Economics, 9(1), 3–18.*

Bekaert, G., Erb, C. and C.H. Harvey, (1997), What matters for emerging equity market investments? *Emerging Markets Quarterly, 17 - 46.*

Bekaert, G. and C.H. Harvey,(1998), Emerging equity market volatility, *Journal of Financial Economics 43, 29 - 78.*

Black, Fischer (1972), Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business*, 45(3), 444–455.

Black, F., Jensen, M, Scholes, M. (1972), The capital asset pricing model: some empirical tests. *Studies in the Theory of Capital Markets, Praeger, New York, NY, 79-124.*

BMF BOVESPA (2013) ; http://www.bmfbovespa.com.br/ capitalizacaobursatil / ResumoBursatilDetalhado. (accessed December 23, 2013)

Borch, Karl (1969). A Note on Uncertainty and Indifference Curves. *Review of Economic Studies, 1969, vol. 36, issue 105, pages 1-4*

Bovespa (2008), Índice Bovespa Definição e Metodologia. São Paulo: Bovespa. Available at http://www.bmfbovespa.com.br/Indices/download/IBovespa.pdf (accessed June 25, 2013)

Brounen, D., De Jong, A., Koedijk, C.G., (2004). Corporate Finance in Europe: Confronting Theory with Practice, *Financial Management 33, 71-101.*

Bruner, R.F., Conroy, R.M., Li, W., O'Halloran, E.F. and Lleras, M.P. (2003), Investing in emerging markets, The Research Foundation, *The Association for Investment Management and Research, Charlottesville.*

Dittmar, R.F., (2002). Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the

Cross Section of Equity Returns. *Journal of Finance 57, 369-403.*

Doan, P., Lin, C., Zurbruegg R., (2009). Pricing assets with higher moments: Evidence from the Australian and US stock markets. *Int.Fin.Markets, Inst. and Money 20, 51 67.*

Estrada, J., (2000). The cost of equity in emerging markets: a downside risk approach, *Emerging Markets Quarterly, 19 - 30.*

Estrada, J. (2002). Systematic risk in emerging markets: the D-CAPM. *Emerging Markets Review 3, 365–379.*

Fama. Eugene F. and James Macbeth. (1973). Risk Return and Equilibrium: *Empirical Tests, Journal of Political Economy 81. 607-636.*

Feldman, R., Kumar, M., (1995). Emerging equity markets: growth, benefits, and policy concerns. *The World Bank Research Observer 10, 181–200.*

Galagedera, D., Brooks, R.D., (2007). Is co-skewness a better measure of risk in the downside than downside beta? Evidence in emerging market data. *Journal of Multinational Financial Management 17, 214–230.*

Graham, John and Campbell Harvey, (2001) The Theory and Practice of Corporate Finance: Evidence from the Field, *Journal of Financial Economics, LX, 187-243.*

Graham, John; Campbell Harvey, (2009) Equity risk premium; Evidence from the Global CFO Outlook survey 2009. *The CFO Global Business Outlook: 1996-2009.*

Gul, F.(1991). A theory of disappointment aversion. *Econometrica 59, 667–686.*

Hamada, R.S. (1972) "The Effect of the Firm's Capital Structure on the Systematic Risk of Common Stocks," The Journal of Finance, 27(2):435-452

Harvey, C.H., Siddique, A., (2000). Conditional skewness in asset pricing tests. *Journal of Finance 60, 1263–1295.*

Harvey, C.H. (1995), Predictable risk and returns in emerging markets, *Review of Financial Studies, 773 - 816.*

Hogan, W. & Warren, J. (1974). Towards the Development of an Equilibrium Capital-Market Model Based on Semivariance. *Journal of Financial & Quantitative Analysis, 9(1), 1-11.*

Huang, C-F., Litzenberger, R., (1988). Foundations for Financial Economics. *North- Holland, New York.*

Ingersoll, J., (1975). Multidimensional security pricing. *Journal of Financial and Quantitative Analysis 10, 785-798.*

Kraus, A., Litzenberger, R.H., (1976). Skewness preference and the valuation of risk assets. *Journal of Finance 31, 1085–1100*

Libby, R. and Fishburn, P. (1977). Behavioral Models of Risk Taking in Business Decisions: A Survey and Evaluation. *Journal of Accounting Research, 15, 272-292.*

Lintner, John (1965). The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics,* 47(1), 13–37.

Markowitz, H.M. (1959). "Portfolio Selection: Efficient Diversification of Investments", New York: John Wiley & Sons.

Nantell T.J., Price K. and Price B. (1982). Mean-Lower Partial Moment Asset Pricing Model: Some Empirical Evidence. *The Journal of Finance Vol. 37, No. 3 (Jun., 1982), pp. 843-855*

Pettengill, G.N., Sundaram, S., Mathur, I., (1995). The conditional relation between beta and returns. *Journal of Financial and Quantitative Analysis 30, 101–116.*

Pereiro, L. (2002). Valuation of companies in emerging markets: a practical approach, *Wiley, New York*.

Pereiro, L. (2006) The Practice of Investment Valuation in Emerging Markets: Evidence from Argentina, *Journal of Multinational Financial Management*, *No.16, pp.160-183.*

Ross, S., Westerfield, R. & Jaffe, J. (2003) *Corporate Finance, Sixth Edition, The McGraw−Hill Companies.*

Roy, A. D. (1952) "Safety-First and the Holdings of Assets", *Econornetrica 20, 431*

Sharpe, Willian F. (1964), Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, *19(3), 425–442.*

Tobin, J. (1958), "Liquidity preference as behavior towards risk", *Review of Economic Studies*, Vol. 26 pp.65-86.

Tsiang, S.C (1972). The Rationale of the Mean-Standard Deviation Analysis, Skewness Preference, and the Demand for Money. *The American Economic Review*, *Vol. 62, No. 3 (Jun., 1972), pp. 354-371*

Appendix: Tables

Table 1: Test Normality							
	All periods				Kolmogorov-Smirnov		
	Mean	**Skew**	**Cskw**	**Var**	**Statistic**	**df**	**Sig.**
BOVESPA	0.0955691	-0.0137639	-0.2556760	0.0003458	0.08	1,849.00	0.00
(EALT4)	0.1527029	0.6202519	-0.1243599	0.0008600	0.17	1,849.00	0.00
(AGEN11)	-1.7487312	3.0070995	-3.4654237	0.0046655	0.28	1,849.00	0.00
(ALPA4)	0.7507811	-1.5725428	-3.0561456	0.0004228	0.09	1,849.00	0.00
(BTOW3)	-1.1410985	0.3638702	0.6754250	0.0010624	0.13	1,849.00	0.00
(BDLL4)	0.1755351	-0.1526503	-3.2057457	0.0005985	0.23	1,849.00	0.00
(BHGR3)	-0.1693011	-0.1696535	-6.3352817	0.0003765	0.20	1,849.00	0.00
(BOBR3)	-0.0852191	-0.0081053	-1.5224290	0.0008042	0.14	1,849.00	0.00
(BMTO4)	1.4586380	1.7353915	-0.6226313	0.0008591	0.23	1,849.00	0.00
(BRFS3)	0.7757708	0.3104107	-0.5250198	0.0005653	0.06	1,849.00	0.00
(BISA3)	-1.2134574	-0.0962052	-1.4798725	0.0009097	0.09	1,849.00	0.00
(HGTX3)	1.8264004	0.6691852	1.2648253	0.0008357	0.09	1,849.00	0.00
(CSAN3)	0.0013786	-0.1482324	-2.1874556	0.0008522	0.08	1,849.00	0.00
(CZLT11)	0.3183293	-1.1740338	-3.3877733	0.0009028	0.16	1,849.00	0.00
(CTNM4)	-0.6841797	-0.0281348	-4.1486334	0.0007564	0.10	1,849.00	0.00
(CPFE3)	0.4458471	-0.0016120	1.5572650	0.0003195	0.06	1,849.00	0.00
(CRDE3)	-0.6727136	-0.3000492	-3.1589293	0.0007835	0.15	1,849.00	0.00
(CREM4)	-0.0618927	0.1286084	-2.6920869	0.0004320	0.13	1,849.00	0.00
(CYRE4)	0.0888042	0.0632004	-0.4320558	0.0011820	0.05	1,849.00	0.00
(ETER3)	1.8269411	14.1342488	-1.6052402	0.0019395	0.20	1,849.00	0.00
(FLCL3)	0.5722480	-0.8266641	-5.5514361	0.0005478	0.14	1,849.00	0.00
(FIBR3)	-0.5764411	-0.6609193	-7.3308112	0.0008683	0.13	1,849.00	0.00
(FRAS4)	0.2776226	1.5110438	-3.0489710	0.0003709	0.16	1,849.00	0.00
(GFSA5)	-0.7822262	0.0163086	0.0643979	0.0014350	0.06	1,849.00	0.00
(HAGA3)	0.9238561	-0.0413309	-3.9516817	0.0003503	0.07	1,849.00	0.00
(HRTP3)	1.1337202	4.6480957	-2.0805361	0.0035150	0.28	1,849.00	0.00
(IGBR5)	-0.3219270	2.2102485	-3.6273670	0.0034286	0.18	1,849.00	0.00
(INEP3)	-1.0974432	32.2605667	2.7839463	0.0109471	0.28	1,849.00	0.00
(INEP4)	-0.2767317	-0.8711761	-2.0456111	0.0010194	0.13	1,849.00	0.00
(MYPK3)	1.5209591	1.4781087	-3.2622454	0.0009270	0.11	1,849.00	0.00
(JHSF3)	-0.0637570	-0.0581249	-0.7131413	0.0010046	0.11	1,849.00	0.00
(KLBN3)	-1.6792987	-1.0911487	-1.8823735	0.0027226	0.22	1,849.00	0.00
(LAME3)	0.1784820	-0.7410813	-2.7677294	0.0005046	0.13	1,849.00	0.00
(MGLU3)	-1.9768607	-0.4479602	-4.4819571	0.0011838	0.10	1,849.00	0.00
(MSPA3)	-0.5569367	-0.7267456	-6.0736993	0.0008104	0.13	1,849.00	0.00
(MNPR3)	-0.2489164	0.0122996	-4.4975823	0.0006498	0.16	1,849.00	0.00
(BNBR3)	0.5681056	0.1469784	1.0797184	0.0004816	0.04	1,849.00	0.00
(PCAR3)	-1.7936800	0.1862252	-3.7804667	0.0014634	0.19	1,849.00	0.00
(RPMG3)	-0.1785904	-0.1763489	-3.9083893	0.0011295	0.09	1,849.00	0.00
(PETR4)	-0.1219548	-0.2248143	-1.5073765	0.0005787	0.06	1,849.00	0.00
(PTBL3)	2.6934222	34.6353663	-1.8828440	0.0055029	0.26	1,849.00	0.00
(RCSL4)	0.1201122	3.1803843	-1.6288655	0.0052653	0.21	1,849.00	0.00
(SNSY5)	0.1935857	0.4363641	1.1374845	0.0022209	0.15	1,849.00	0.00

(PSEG3)	-0.0497066	0.3623898	-1.3192369	0.0007291	0.16	1,849.00	0.00
(SULT3)	-1.1489879	-0.5255012	-6.0203274	0.0005676	0.19	1,849.00	0.00
(TCNO3)	-0.1251993	-0.5771915	-4.5913666	0.0010692	0.11	1,849.00	0.00
(TEKA4)	-0.2437625	0.5780466	0.6516543	0.0026386	0.22	1,849.00	0.00
(TUPY3)	-0.3811373	1.3553645	-1.2832706	0.0061904	0.27	1,849.00	0.00
(MWET4)	-0.8022700	-0.2085142	1.3987691	0.0010679	0.24	1,849.00	0.00
(WHRL4)	1.1184160	-0.3830670	-2.2228907	0.0017631	0.19	1,849.00	0.00

Note: Returns are average daily returns is (x10^3) and skewness is (x10^3)

Table 2: Share portfolios ranked by skewness of returns

ALL PERIODS					*UPTURN PERIODS*					*DOWNTURN PERIODS*				
Portfolio	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**
1	0.586	9.88	-1.84	3.74	**1**	2.624	8.67	-1.24	5.78	**1**	-0.040	0.72	-0.54	1.48
2	-0.009	0.50	-0.22	1.70	**2**	0.678	0.87	-2.05	2.21	**2**	-0.289	0.12	-1.20	1.36
3	-0.162	-0.01	-1.93	0.77	**3**	0.429	0.33	-2.28	0.53	**3**	-0.593	-0.13	-0.88	0.86
4	-0.225	-0.27	-3.12	0.86	**4**	0.374	0.07	-2.00	0.65	**4**	-0.999	-0.33	-3.28	0.79
5	-0.326	-0.89	-3.96	1.06	**5**	0.359	-0.81	-3.12	1.20	**5**	-1.130	-1.66	-4.64	0.88
1-5	0.912*	10.77**	2.12	2.68	**1-5**	2.265**	9.47***	1.88	4.57	**1-5**	1.090**	2.38**	4.10	0.60

Note: This table lists equally weighted average excess returns and risk characteristics of quintile portfolios formed from shares ranked by skewness of share returns. All risk measures are estimated over the same semesters as average realized returns. We show, in row 1–5, differences in values between highest and lowest ranked portfolios. We use t-statistics to test for significant differences between highest and lowest ranked portfolio average returns. We also test for evidence of differences between levels of skeweness in upturn and downturn periods. To validate T-test we previously confirm normality using Shapiro-Wilk test for each portfolio.
Returns are average daily returns (x10^3). Skewness is (x10^3) and variance is (x10^3).
*Statistically significant differences, at the 10% level.
**Statistically significant differences, at the 5% level.
***Statistically significant differences, at the 1% level.

Table 3: Share portfolios ranked by variance of returns

ALL PERIODS					*UPTURN PERIODS*					*DOWNTURN PERIODS*				
Portfolio	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**
1	-0.133	8.12	-1.13	4.71	**1**	1.890	7.55	-0.57	7.71	**1**	-1.491	0.41	-1.61	2.43
2	-0.377	1.30	-1.89	1.33	**2**	1.565	1.01	-2.24	1.07	**2**	-0.928	0.03	-1.28	1.41
3	0.315	0.15	-1.99	0.90	**3**	0.674	0.17	-2.60	0.67	**3**	-1.045	-0.37	-2.87	1.27
4	-0.262	-0.13	-3.20	0.68	**4**	0.284	0.32	-2.94	0.51	**4**	-0.475	-0.08	-3.06	0.81
5	0.387	-0.17	-2.75	0.42	**5**	0.423	0.14	-2.59	0.33	**5**	0.255	-0.84	-1.38	0.48
1-5	-0.520	8.30	1.62	4.28***	**1-5**	1.46*	7.41	2.02	7.38***	**1-5**	-1.74**	1.25	-0.23	1.95***

Note: This table lists equally weighted average excess returns and risk characteristics of quintile portfolios formed from shares ranked by variances of share returns. All risk measures are estimated over the same semesters as average realized returns. We show, in row 1–5, differences in values between highest and lowest ranked portfolios. We use t-statistics to test for significant differences between highest and lowest ranked portfolio average returns. We also test for evidence of differences between levels of variance in upturn and downturn periods. To validate T-test we previously confirm normality using Shapiro-Wilk test for each portfolio.
Returns are average daily returns (x10^3). Skewness is (x10^3) and variance is (x10^3).

Table 4: Share portfolios ranked by coskewness of returns

ALL PERIODS					*UPTURN PERIODS*					*DOWNTURN PERIODS*				
Portfolio	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**	**Portfolio**	**Return**	**Skew**	**Cskw**	**Var**
1	-0.09	3.49	1.05	2.19	**1**	1.97	6.10	0.27	5.93	**1**	-0.31	0.18	2.54	1.24
2	0.22	1.76	-1.10	1.48	**2**	1.06	2.18	-1.60	1.94	**2**	-0.67	-0.02	-0.17	1.04
3	0.35	4.09	-2.24	2.19	**3**	0.25	0.53	-2.50	1.11	**3**	-0.74	0.15	-2.37	1.43
4	-0.10	0.35	-3.48	1.47	**4**	0.85	-0.10	-3.10	0.59	**4**	-1.24	0.19	-4.11	2.18
5	-0.55	-0.44	-5.45	0.76	**5**	0.99	0.52	-4.16	0.75	**5**	-1.32	-0.48	-6.14	0.97
1-5	0.46	3.93	6.49***	1.43	**1-5**	0.98	5.58	4.43***	5.18	**1-5**	1.01*	0.660	8.67***	0.27

Note: This table lists equally weighted average excess returns and risk characteristics of quintile portfolios formed from shares ranked by co-skewness of share returns. All risk measures are estimated over the same semesters as average realized returns. We show, in row 1–5, differences in values between highest and lowest ranked portfolios. We use t-statistics to test for significant differences between highest and lowest ranked portfolio average returns. We also test for evidence of differences between levels of co-skeweness in upturn and downturn periods. To validate T-test we previously confirm normality using Shapiro-Wilk test for each portfolio.
Returns are average daily returns ($x10^3$). Skewness is ($x10^3$) and variance is ($x10^3$).

Table 5: Share portfolios ranked by beta of returns

ALL PERIODS					*UPTURN PERIODS*					*DOWNTURN PERIODS*				
Portfolio	**Return**	**ß**	**Cskw**	**Var**	**Portfolio**	**Return**	**$ß^+$**	**Cskw**	**Var**	**Portfolio**	**Return**	**$ß^-$**	**Cskw**	**Var**
1	-0.72	1.01	-1.78	1.08	**1**	0.93	1.02	-1.84	4.05	**1**	-1.43	1.14	-0.71	1.43
2	0.30	0.67	-2.00	2.25	**2**	0.86	0.58	-2.33	1.73	**2**	-0.75	0.74	-3.01	1.38
3	0.38	0.54	-1.97	1.32	**3**	0.90	0.47	-2.05	2.29	**3**	-0.63	0.55	-1.79	1.34
4	0.06	0.42	-2.25	1.88	**4**	0.82	0.38	-2.27	0.66	**4**	-0.61	0.41	-1.83	1.86
5	-0.14	0.24	-2.98	1.64	**5**	0.73	0.23	-2.12	1.87	**5**	-0.52	0.21	-4.64	0.58
1-5	-0.58	0.76***	1.21	-0.56	**1-5**	0.20	0.78***	0.28	2.19	**1-5**	-0.90*	0.92***	3.93	0.84

Note: This table lists equally weighted average excess returns and risk characteristics of quintile portfolios formed from shares ranked by beta of share returns. All risk measures are estimated over the same semesters as average realized returns. We show, in row 1–5, differences in values between highest and lowest ranked portfolios. We use t-statistics to test for significant differences between highest and lowest ranked portfolio average returns. To validate T-test we previously confirm normality using Shapiro-Wilk test for each portfolio.
Returns are average daily returns ($x10^3$). Skewness is ($x10^3$) and variance is ($x10^3$).

Table 6: t-test for Equality of Means in ß upturns periods and ß downturn periods

					95% Confidence Interval of the Difference	
t	**df**	**Sig. pvalue**	**Mean Difference**	**Std. Error Difference**	**Lower**	**Upper**
-1,645	85	**,104**	-,1079281637	,0656164047	-,2383911554	,0225348280

Note: In this table we test for evidence of differences between levels of beta in upturn and downturn periods. The null hypothesis cannot be rejected, but worth noting the proximity of Pvalue to 10%.