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The Inconvenient Truth of the Downside Beta

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Abstract

In this thesis, we perform a robustness test of the interesting findings by in particular Artavanis (2013), but also Ang et al. (2006) and others, who find evidence that a downside beta outperforms the CAPM beta in its ability to explain excess stock returns in a test developed by Fama and French (1992). Stating that the CAPM beta is outperformed by the less known downside beta is a bold statement, and could indicate that information of a downside beta can be used to achieve abnormal excess returns on the stock market. These findings deserve robustness tests to either strengthen their case or show that the results are inconsistent across different markets or time periods, which is the motivation for writing this thesis. Our main findings show that there is no difference in the ability of the CAPM beta and the downside beta to explain excess returns in a Fama and French (1992) test during the years 2000-2014 on the Frankfurt, London and Stockholm stock exchanges. Thus, the results of the robustness test are demotivating, weakening the case for the downside beta rather than accepting its superiority.

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1 Introduction

Portfolio optimization is an important part of financial theory, still to this day heavily influenced by early financial theorists such as Harry Markowitz and William Sharpe, amongst others. In a seminal article, Markowitz (1952) introduces the portfolio selection problem as a two-stage process where the individual seeks to maximize expected returns while minimizing the variance of returns. Markowitz's model is widely accepted within the literature, and was the foundation for the famous Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965) and Black (1972) (SLB). SLB show that the expected return of any security can be compared to the risk free return and the expected market return by means of the security's beta value, where beta is the correlation of a security's excess return to the excess return achieved by the market portfolio.

The beta value has had a large impact on financial theory and on the financial industry. It is one of the key statistics used to present or describe a particular stock (for example, Yahoo Finance presents 15 statistics of which beta is one, in its stock overview).

By taking a step back, rather than accepting the popular mean – variance and CAPM theories, and focusing on what an investor actually wants to achieve with portfolio optimization, it is relevant to ask whether or not Markowitz (1952/1959) was right in using the return – variance trade-off. The ultimate aim for someone building an investment portfolio must be to optimize the return relative to the risk. Markowitz (and subsequently SLB in the CAPM model) used variance as the measure of risk, and this is where some see a weakness of the model. Variance includes both gains and losses, and the models see both large gains and large losses as equally bad. Why would an investor be equally worried about large gains and large losses? In fact, Markowitz (1959) proposes an alternative measure, called semi-variance, which only focuses on downside variance as a measure of risk. Although pointing out several benefits with semi-variance, Markowitz (1959) bases his theory on normal variance due to its easier computation and it being more well-known than semi-variance. However, research of portfolio optimization based on semi-variance did not end with Markowitz (1959). Several authors have dwelled into the subject, among the more well known, Hogan and Warren (1974) develop a downside beta value based on semi-covariance.

The CAPM beta value has been criticized by Fama and French (1992), who show that when one controls for firm size and book-to-market value of equity, the beta value does not explain the excess returns on the US stock market in the years 1963-1990. Several authors have since looked into other risk measures, and in particular conditional beta and downside beta, which has been found to better explain excess return than the CAPM beta, see for example Howton & Peterson (1998), Ang et al. (2006), Pettengill, Sundaram & Mathur (2002) and Artavanis (2013).

To either strengthen the validity of the downside beta or to weaken its case against the CAPM beta, we perform a robustness test of the findings of Artavanis (2013) and Ang et al. (2006) who both use the US market in their studies. We develop the research further by testing whether a downside beta approach for estimating risk better explains excess return than the CAPM beta on the Frankfurt, London and Stockholm stock exchanges in order to test if the superiority of the downside beta is consistent across different markets.

To summarize, the thesis tests the following research question:

- Does a downside beta better explain excess returns than the CAPM beta on the Swedish, German and Brittish stock markets?

We find no evidence that suggests that the (Hogan-Warren) downside beta outperforms the CAPM beta in its ability to explain cross-sectional excess returns in a Fama and French (1992) test on the Frankfurt, London and Stockholm stock exchanges in the years 2000-2014. In the cross-sectional regressions, the coefficients for the downside beta and the CAPM are similar in magnitude and statistical significance, in no occasion is one statistically significant when the other is not. Thus, the results of the robustness test are demotivating, weakening the case for the downside beta rather than accepting its superiority.

We also find that size is positively related to excess returns in Frankfurt and Stockholm during the years 2000-2014, whereas the size effect is insignificant in London. Conversely, the book-to-market value is positively related to excess returns in London and Stockholm, but not in Frankfurt. The fact that the results differ in the different markets is proof that the results of Fama and French (1992) are not universal across markets. The analysis shows some weaknesses of the test itself. In particular, the results are sensitive to the market performance in the tested time period.

The remainder of this thesis is organized as follows: In order to familiarize the reader with the subject, Chapter 2 presents the relevant literature subsectioned in a chronological order, including the return – variance trade-off in portfolio optimization, the capital asset pricing model, critique of the CAPM and semi-variance and downside beta. Chapter 3 expands the theories presented in Chapter 2 in a mathematical format. The data and the methodology are discussed in Chapter 4. Chapter 5 presents and analyses the results obtained in the study, and the thesis is concluded in Chapter 6.

2 Literature Review

This chapter summarizes relevant literature in order to set the frame for the subsequent chapters of the thesis. The relevant literature has been divided into four parts; Return – variance trade-off in portfolio optimization, The Capital Asset Pricing Model, Critique of the CAPM and Semi-variance and downside beta.

2.1 Return – variance trade-off in portfolio optimization

Markowitz (1952) defines the portfolio selection process in two steps, where in a first step an investor forms his beliefs about future performance, and in the second step chooses his portfolio based on those beliefs. How such beliefs are formed is not thoroughly discussed by Markowitz (1952), who rather focuses on the second step – that of portfolio selection.

The aim of portfolio optimization is to minimize the risk given an expected level of return, or analogously maximize expected return given an expected level of risk, which Markowitz (1952) defines as the variance in returns around its expected value. An efficient portfolio is a portfolio in the attainable set (all possible combinations of securities) such that the expected return cannot be increased without increasing the expected variance, and the expected variance cannot be decreased without decreasing the expected return. Figure 1 plots expected return versus expected variance, where the efficient portfolios are the ones on the border of the top left part of the attainable set (Markowitz, 1952/1959).

The rationale in Markowitz (1952/1959) for reducing risk when pooling several securities in a portfolio is (perhaps self-evidently) that returns across securities are not perfectly correlated. That is, when one security increases in value, another might decrease, which when aggregated into a portfolio decreases the total variance of the portfolio returns. However, since security returns are almost always positively correlated, aggregating securities into a portfolio can never completely eliminate the risk. The systematic risk will always be present even in an optimized portfolio (Sharpe, 1964). Further, due to market limitations, not even the idiosyncratic risk can be completely diversified away.

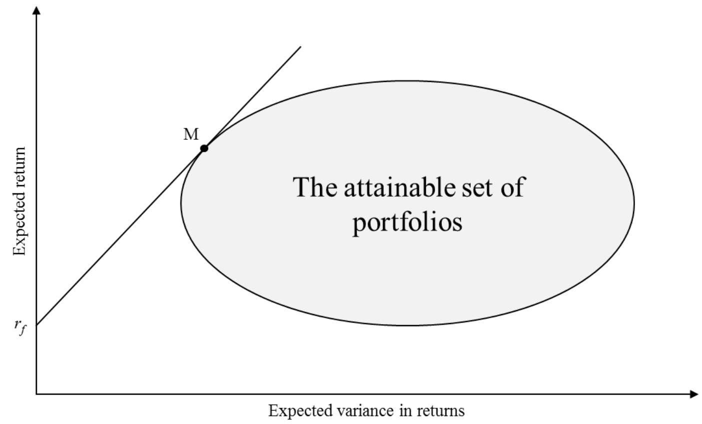

Figure 1: The return – variance trade-off. The attainable set of portfolios depicting the return – variance trade-off for investors choosing portfolios. If investors are rational, allowed to borrow at the risk free rate, r_f, and agree on preferences, favouring high returns and low variance, the market portfolio must be the tangency portfolio M. Based on the work by Markowitz (1952/1959), Sharpe (1964) and Lintner (1965).

In the final part of his book, Markowitz (1959) shows his analysis based on semi-variance rather than variance. Semi-variance is defined as the variance measured as the average of the squared negative deviations from the expected returns only (more on this in a later chapter). Markowitz (1959) argues that this approach focuses on reducing losses, rather than reducing pure volatility, and even proceeds to state that:

"Analyses based on S [semi-variance] tend to produce better portfolios than those based on V [variance]" (Markowitz, 1959)

However, among the downsides of using semi-variance are its larger complexity, it being less well-known and its more demanding computing methods, taking two to four times longer to perform on a "high speed electronic computer" (Markowitz, 1959).

2.2 The Capital Asset Pricing Model

Markowitz (1952/1959) does not discuss in detail what particular portfolio in the efficient set an investor should choose. Sharpe (1964) and Lintner (1965) use the model of Markowitz and add a risk free security and the assumption that all investors agree on expected returns, variances and covariances. When an investor can lend and borrow at the risk free rate, Sharpe (1964) shows that there will only be one particular portfolio chosen by each and every investor. Given that an investor has a utility function that increases in expected return and decreases in expected variance, where both inputs have a marginally decreasing effect on the utility, the optimum portfolio is the one in the efficient set that is tangent to a straight line between the efficient set and the risk free rate, as seen in Figure 1. This line is commonly referred to as the Capital Market Line. The total risk level is adjusted by lending or borrowing at the risk free rate (Sharpe, 1964).

The portfolio called M in Figure 1 is shown by Lintner (1965) to be the market portfolio. Since all investors agree on future prospects, they all invest in portfolio M and adjust their level of risk by lending or borrowing at the risk free rate. Thus in order to achieve market equilibrium, portfolio M must be the market portfolio. The weights of each particular stock in the market portfolio are the market values of each individual stock divided by the aggregate market value of all stocks (Lintner, 1965).

Having defined the optimal portfolio choice, Sharpe (1964) shows that since a portfolio is a linear combination of a number of securities, and that, in theory, all non-systematic risk can be diversified away, the only risk that should be considered for a particular stock is how it covaries with the market. That is, for a relatively safe security, which is rather independent of the market performance, an investor can accept a low expected return. On the other hand, for an investor to accept a security that covaries strongly with the market, an investor requires a large expected return. Although not using the word beta, Sharpe (1964) defines the movement in relation to the efficient portfolio as the correlation between the returns of the security and the returns of the market, which has later become the well-known CAPM beta.

2.3 Critique of the CAPM

Sharpe (1964), Lintner (1965) and Black (1972) concluded that stocks with a high beta value should be rewarded with a large expected return, and that no other risk measure should be necessary, a conclusion that has received critique from several academics since. Fama and MacBeth (1973) test the CAPM model by regressing monthly returns on beta values, squared beta values and the residuals from the market model, which in turn regresses individual excess stock returns solely on the market excess return.

The dataset used by Fama and MacBeth (1973) stretches from 1926 to 1968 and contains approximately 700 stocks divided into 20 portfolios throughout the period. The whole sample is needed to show a statistically significant positive coefficient for the beta value. For shorter periods, such as five to ten years, the coefficient for the beta value is generally not statistically significant.

From their results, Fama and MacBeth (1973) cannot reject the hypothesis that a higher beta yields linearly higher expected returns. However, although the results are not clear-cut, Fama and MacBeth (1973) show that the constant term in the regressions is statistically significantly different from the risk free rate, in contrast to what is predicted by the CAPM.

In a later and well-known test of the CAPM, Fama and French (1992) enhance the Fama-MacBeth regressions with additional explanatory variables, using US data from 1963 to 1990, which yields different results than was obtained by Fama and MacBeth (1973). Fama and French (1992) argue that stocks of different size (market value) have different betas. When controlling for market value of equity (ME) as a proxy for size, book-to-market value of equity (BE/ME), leverage and the earnings-to-price ratio (E/P), Fama and French (1992) find no statistical significance for the coefficient of the beta value in the Fama-MacBeth regressions, and the authors state that:

"In a nutshell, market β seems to have no role in explaining the average returns on NYSE, AMEX, and NASDAQ stocks for 1963-1990, while size and book-to-market equity capture the cross-sectional variation in average stock returns that is related to leverage and E/P"

2.4 Semi-variance and downside beta

As was already noted by Markowitz (1959), there might be other measures of risk that are more appropriate for portfolio optimization than pure variance. In particular, Markowitz (1959) suggested semi-variance as an alternative measure of risk. Unlike unconditional variance, semi-variance considers only observations below a certain threshold, normally; zero, the risk free rate or the expected return of the market.

If the return distribution is symmetrical, the variance and the semi-variance framework produce the same results. However, when the return distribution is asymmetrical, especially shown for a lognormal distribution by Price et al. (1982), the two frameworks diverge.

A downside beta risk measure based on semi-covariance is appealing because a security is not necessarily considered more risky by an investor when performing extraordinarily well at the same time as the market, as the CAPM beta based on covariance would have us believe. Nor does it consider poor security performance while the market is performing well risk reducing, as the conventional beta does (Artavanis, 2013). Hence, downside beta only attributes adverse outcomes as risk increasing. Even though an investor might consider abnormal positive returns as risk increasing, he will put more emphasis on negative abnormal returns due to decreasing absolute risk aversion as shown by Post and van Vliet (2004), and loss aversion (Artavanis, 2013). Figure 2 shows how the CAPM beta (all four quadrants) and the Hogan-Warren downside beta (the leftmost quadrants) are affected by different co-movements of the portfolio returns and the market returns.

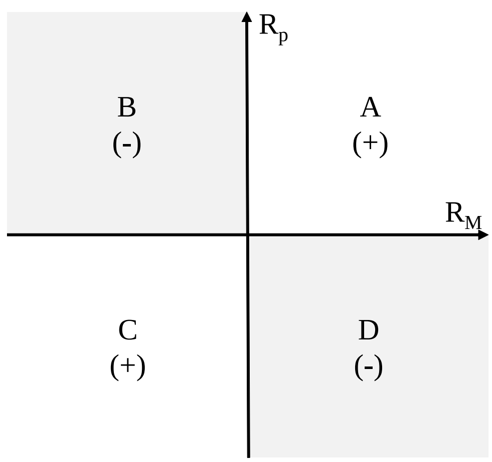

Figure 2: Covariance and beta. The different quadrants show how the CAPM beta is affected by different observations of the relation between portfolio returns, R_p, and the market returns, R_m. In quadrant B and D, the portfolio covaries negatively with the market, which decreases the CAPM beta and thus the perceived risk of the portfolio decreases. In quadrants A and C, the portfolio covaries with the market and the CAPM beta increases. The fact that the CAPM risk measure increases (decreases) in quadrant A (D) is unintuitive as investors generally prefer profits over losses regardless of the market performance. The Hogan-Warren downside beta, based on semi-covariance, ignores outcomes when the market return is positive and is thus alleviated from the unintuitive quadrants A and D.

Over the years, a few different versions of downside beta have emerged. Hogan and Warren (1974) use the risk free rate of return (which can be seen as an opportunity cost of capital) as the threshold when they show that semi-variance can replace variance to measure portfolio risk without losing the fundamental structure of the CAPM. In this setting, the efficient portfolios are those that minimize the semi-variance given the expected return, and the only risk that rewards higher expected return is the co-movement with the market when the market performs below the threshold (Hogan and Warren, 1974). The corresponding downside beta is known as the Hogan-Warren downside beta.

Estrada (2002) presents a different version of the downside beta, where the numerator is given by the covariance of the security return and the market return conditional on both the security and the market performing below their expected returns. A reason for this specification is to avoid the inconvenience of an asymmetrical semi-covariance matrix that for example the Hogan-Warren approach produces (Artavanis, 2013).

In a framework similar to that of Hogan and Warren (1974), Ang et al. (2006) build their model on a representative agent with a "rational disappointment aversion utility function". In the framework of Ang et al. (2006), an investor would be disappointed if he does not get at least his certainty equivalent (the risk free rate of return) back from an investment. In addition, the authors condition the semi-covariance on the market performing worse than its average excess return.

In his treatise on downside risk, Artavanis (2013) methodologically examines and compares the different recipes of downside beta with each other and the CAPM beta. Artavanis (2013) finds that the Hogan-Warren beta is the only specification that is consistent with the CAPM framework and state-preference theory.

In Estrada's (2002) framework, all risk reducing observations when the market underperforms while the security outperforms the threshold are excluded from the sample. Thus, the framework systematically overestimates the downside risk and it additionally strips the available dataset of observations resulting in increased estimation errors (Artavanis, 2013).

The inclusion of two separate thresholds for the estimation of semi-covariance in the framework of Ang et al. (2006) is shown by Artavanis (2013) to violate state-preference theory. In particular, the problem arises from what he describes as a "region-sign bias", where in marginally bad states the return of the security has the opposite effect on the risk premium than what would seem logical.

After having theoretically presented why the Hogan-Warren beta is preferable, Artavanis (2013) also presents empirical evidence of its superiority contra both its semi-covariant challengers and the CAPM beta by the use of Fama-MacBeth regressions on US data from 1926 to 2010.

Howton and Peterson (1998) perform a Fama and French (1992) test on US data from 1977 to 1993 on both the CAPM beta and a dual-beta model developed by Bhardwaj and Brooks (1993). Howton and Peterson (1998) divide the sample into two sub-samples; up markets and down markets. Up markets are defined as months when the market return is higher than the median market return, and down markets are defined as months when the market return is lower than the median market return. Howton and Peterson (1998) find that a beta value calculated during months with market returns below the average market return is statistically significantly negatively related to excess returns in bear markets, whereas the opposite holds in bull markets for beta values calculated in months with market excess returns above their average. Pettengil, Sundaram and Mathur (2002) perform a similar test to Howton and Peterson (1998), although dividing the sample into sub-samples according to; up markets – when the monthly market return minus the US one-month treasury bill is larger than zero, and down markets – when the monthly market return minus the US one-month treasury bill is smaller than zero. PSM (2002) find that the CAPM beta is not statistically significantly related to excess returns across the entire sample period. In accordance with Howton and Peterson (1998), PSM (2002) find that when the sample is divided into sub-samples, bear (bull) beta is statistically significantly negatively (positively) related to excess returns in down (up) markets. However, in the same sub-samples, the CAPM beta is even more significant. Thus, PSM (2002) come to the conclusion that sub-sampling is sufficient for beta to become significantly related to excess returns.

3 Theory

This chapter presents the theories discussed in Chapter 2 in a mathematical format.

3.1 Mean – variance and mean – semi-variance

An efficient portfolio is one that minimizes the expected variance, given the expected return. Markowitz (1959) presents a general example with n securities. The expected return of a portfolio is defined as

$$E = \sum_{i=1}^{n} X_i \mu_i \tag{1}$$

where μ_i is the expected return of security i and X_i is the relative amount invested in security i, such that

$$\sum_{i=1}^{n} X_i = 1 \tag{2}$$

and

$$X_i \geq 0 \;\forall\; i \tag{3}$$

which ensures no short-selling. The expected variance of a portfolio is therefore

$$V = \sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j \sigma_{ij} \tag{4}$$

where σ_{ij} is the covariance of the returns of security i and security j.

The problem of determining the efficient frontier is then to maximize expected return $\sum_{i=1}^{n} X_i \mu_i$ given the expected variance $V = \sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j \sigma_{ij}$, or likewise minimize expected variance given the expected return. This can be achieved by a number of programming techniques, for example a linear programming model or Monte Carlo techniques (Markowitz, 1959). The resulting efficient frontier can then be plotted in the return – variance space as in Figure 1 above.

When analyzing a mean – semi-variance efficient frontier, Equations (1)-(3) are used as defined above, although Equation (4) needs to be rewritten. Markowitz (1959) defines

$$r^{-} = \begin{cases} r \text{ if } r \leq 0 \\ 0 \text{ if } r > 0 \end{cases} \tag{5}$$

where r is returns. A portfolio's semi-variance is then defined as

$$S_o = \sum_i \sum_j s_{ij} \left(t_1, ..., t_k\right) X_i X_j \tag{6}$$

where the semi-covariance between security i and j is calculated by

$$s_{ij} \left(t_1, ..., t_k\right) = \frac{1}{T} \sum_{k=1}^{K} r_{it_k} r_{jt_k} \tag{7}$$

where the index t represents time period (year, month etc.), T is the total number of time periods studied and K is the number of time periods where the market has negative returns.

Markowitz (1959) shows the rationale for using semi-variance rather than variance by a discussion of distributions. Consider the two distributions of returns in Figure 3 below.

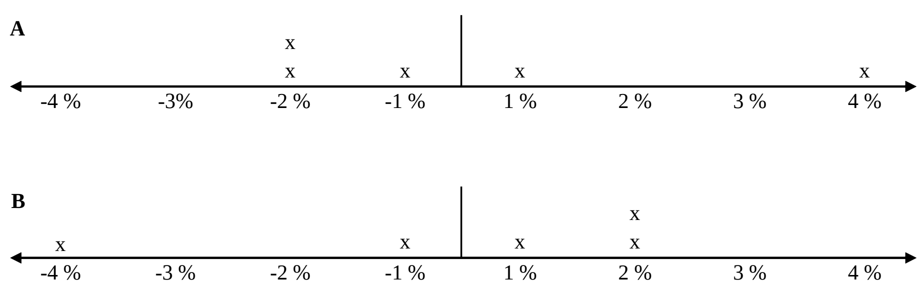

Figure 3: Distribution, variance and semi-variance. The variance of the observations (denoted by x in the figure) is the same for both distribution A and its reflection B, whereas the downside semi-variance is larger in distribution B as it is negatively skewed due to the larger outlier. Thus, an investor who bases his portfolio decision on variance would be indifferent between the two portfolios, whereas if he uses semi-variance he would prefer portfolio A.

The variance of distribution A is the same as that of distribution B, whereas the semi-variance is larger for distribution B than for distribution A. A mean – variance analysis considers the two cases equally desirable, whereas a semi-variance analysis would favor distribution A. In short, an analysis based on semi-variance choses the distribution most skewed to the right (positively skewed) for each given expected return.

3.2 Beta and downside beta

The classical CAPM equation developed by Sharpe (1964), Lintner (1965) and Black (1972) is defined as

$$E\left(R_i\right) = R_f + \beta_i \left[E\left(R_m - R_f\right)\right] \tag{8}$$

where index i represents security i, index f represents the risk free asset and index m represents the market portfolio. In Equation 8, β_i is defined as

$$\beta_i = \frac{cov\left(R_i, R_m\right)}{var\left(R_m\right)} \tag{9}$$

There are several definitions of downside beta, an early version is the Hogan-Warren downside beta developed by Hogan and Warren (1974), which according to Artavanis (2013) is the only specification consistent with the framework prescribed by Markowitz (1959) and state-preference theory. The Hogan-Warren equivalent to Equation 9 is

$$\beta_i^- = \frac{cov\left(\left(R_i - R_f\right) \cdot \min\left(R_m - R_f, 0\right)\right)}{var\left(\min\left(R_m - R_f, 0\right)\right)} \tag{10}$$

3.3 Tests of the CAPM beta and the downside beta

Fama and MacBeth (1973) regress monthly portfolio returns on portfolio beta values (expressed as the average of the betas of the individual securities in each portfolio), the average of the squared security beta values for each portfolio and the average of the standard error of the residuals in each market model regression for each portfolio. Fama and MacBeth (1973) use the market model

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \tag{11}$$

where $R_{m,t}$ is the excess market return in period t, $R_{i,t}$ is the excess return of security i in period t and $\epsilon_{i,t}$ is the residual of the regression in period t. Since $\beta_i = \frac{cov(R_i,R_m)}{var(R_m)}$ and by construction $cov\left(\epsilon_i, R_m\right) = 0$, then

$$var\left(R_i\right) = \beta_i^2 var\left(R_m\right) + var\left(\epsilon_{i,t}\right) + 2\beta_i cov\left(R_m, \epsilon_{i,t}\right) \quad (12)$$

i.e, from Equation 12, $var\left(\epsilon_{i,t}\right)$ is the only factor determining the distribution of the returns that is not related to beta for security i.

The Fama-MacBeth regressions in their full form are then defined as

$$R_{pt} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_{p,t-1} + \hat{\gamma}_{2t}\hat{\beta}^2_{p,t-1} + \hat{\gamma}_{3t}\bar{s}_{p,t-1}\left(\hat{\epsilon}_i\right) + \hat{\eta}_{p,t} \quad (13)$$

where $\hat{\beta}_{p,t-1}$ is the average of the betas in portfolio p derived from Equation 11 in period $t-1$ and $\bar{s}_{p,t-1}\left(\hat{\epsilon}_i\right)$ is the standard error of the residuals also obtained from Equation 11. Fama and MacBeth (1973) find that the coefficients for $\hat{\beta}^2_{p,t-1}$ and $\bar{s}_{p,t-1}\left(\hat{\epsilon}_i\right)$ are insignificantly different from zero.

The test statistic used to test the significance of the coefficients of regression 13 in Fama and MacBeth (1973) is

$$t\left(\bar{\hat{\gamma}}_j\right) = \frac{\bar{\hat{\gamma}}_j}{\frac{s\left(\hat{\gamma}_j\right)}{\sqrt{n}}} \quad (14)$$

where n is the number of months in the test period.

Fama and French (1992) build on the research of Fama and MacBeth (1973) by adding additional explanatory variables to the Fama-MacBeth regressions. Market value of equity, book-to-market value of equity, leverage and the earnings-to-price ratio are all included as additional risk factors. To distinguish between the effects of size and beta in average returns, Fama and French (1992) adopt a double sorting procedure by first sorting the securities according to size, and then, within each size category, an additional sorting on pre-ranking betas for the individual stocks. Thus, Fama and French (1992) use a similar sorting procedure as Fama and MacBeth (1973) with the addition of the initial sorting on size (ME). The average betas within each size – beta sorted portfolio are then given to each individual security within the particular portfolio in order to avoid imprecise beta estimates for individual securities. These beta values are used along with security specific data on ME, BE/ME, E/P and leverage in cross-security regressions. Portfolios are updated yearly, as well as ME, BE/ME, leverage and E/P for each security. The beta values and the natural logarithms of the other explanatory variables are then regressed on the next twelve monthly returns for each security. The process is repeated for each year, and time-series averages of each cross-sectional coefficient are calculated along with t-statistics according to Equation 14 (Fama and French, 1992).

Fama and French (1992) find that the coefficient for beta is not statistically significant, with a t-statistic of only -0.46. Further, they find that the coefficients for $\log(ME)$ and $\log(BE/ME)$ are significantly different from zero and that these variables combined absorb the explanatory power of leverage and E/P.

Thus, Fama and French (1992) find no evidence that supports using the CAPM model to explain excess returns in cross-sections. Artavanis (2013) shows that when performing the Fama-MacBeth regressions on downside beta instead of the CAPM beta, the downside beta remains statistically significant even in Fama and French (1992) regressions.

4 Data and Methodology

This chapter presents the data sources and the specific data, as well as the econometric techniques used to answer the research question in Chapter 1. Although this chapter only describes the process of sorting on size and beta, sorting has also been performed equivalently on the BE/ME and beta.

4.1 Data sources and the dataset

We use Bloomberg to obtain the monthly returns adjusted for dividends and all other corporate actions, the market value of equity (ME) and the book-to-market value (BE/ME) for all traded stocks included in the all-share indices on the Frankfurt, London and Stockholm stock exchanges from 1995 to 2014. Securities with missing data throughout the entire time period of either ME, BE/ME or returns are excluded from the data set. Further, securities with recordings of negative book values are also excluded from the data set, as in Fama and French (1992), the number of such securities is small. Only the most frequently traded security of each company is included in the data set, i.e. usually shares of class B. The risk free rates are the one-month interbank rates for the respective markets, also obtained from Bloomberg.

4.2 The Fama-French test

For the three markets specified above, we test if the CAPM beta and the Hogan-Warren downside beta explain cross-sectional excess returns in the presence of the logarithm of the market value of equity and the logarithm of the book-to-market ratio. Based on the results of Fama and French (1992), we do not include the earnings-to-price ratio or the leverage. The cross-sectional regressions in their full form are specified as

$$R_{i,t} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_p + \hat{\gamma}_{2t} \ln(ME_{i,Dec}) + \hat{\gamma}_{3t} \ln(BE/ME_{i,Dec}) + \varepsilon_t \qquad (15)$$

where Dec refers to that the explanatory variables are taken from December in the year before the returns (the dependent variable) were observed. The cross-sectional regressions are performed monthly over the entire time period, except for the first five years that are used for pre-ranking security betas. A detailed description of the process follows below.

4.2.1 The sorting process

For each year, after an initial security beta pre-ranking period of five years, the different securities are first sorted into septiles depending on their market capitalization in December of the previous year. Since the number of securities is not usually divisible by the number of size sorted portfolios, the largest and the smallest size portfolios receive one extra security. Fama and French (1992) use fixed market capitalization limits to sort into size sorted portfolios rather than using our approach of assigning an equal number of stocks into each portfolio. The size sorting approach by Fama and French (1992) yields too few securities in some of the size sorted portfolios, which prevents further beta sorting and is thus not used in our analysis. This difference in sorting methodology is unlikely to affect the outcome of the analysis. Security betas are calculated from a pre-ranking period of 60 months, using Equation 9. Within each size sorted portfolio, a sorting of the pre-ranking betas is performed. The same method of dealing with indivisibility as when sorting on size is applied to the beta sorting. In order for a security to be included in this sorting, it must have data on market value for December of the year in which the pre-ranking of the beta values ends and monthly returns for the pre-ranking period and the following twelve months. By performing this check yearly, we avoid any survivorship bias from the easier solution to only analyze securities with data for the full sample period.

4.2.2 Estimating the portfolio betas

The equal weighted monthly excess returns are calculated for each portfolio and month in the data set after the initial pre-ranking period. The post-ranking portfolio excess returns are regressed across the entire data set, using the market excess return for each month and its first lag as explanatory variables.

$$R_{p,t} = \theta_0 + \theta_1 R_{M,t} + \theta_2 R_{M,t-1} + \varepsilon_t \tag{16}$$

The market return at time t for each market is defined as the value weighted returns of the securities in the data set without missing data on either returns or market capitalization at time t. The CAPM portfolio beta is calculated, identically to the specification in Fama and French (1992), as the sum of the slopes of the regression coefficients for the market excess return, θ_1, and the coefficient of its first lag, θ_2. For Downside beta, Equation 10 is used to define the post-ranking portfolio downside betas.

4.2.3 The Fama-MacBeth regressions

Fama-MacBeth regressions specified according to Equation 15 are performed for each month of the dataset after the initial pre-ranking period. For each year, securities are sorted into portfolios as was described in chapter 4.2.1 and are then assigned the post-ranking beta of the portfolio to which they are assigned. By re-sorting the portfolios yearly, a security can move across portfolios depending on changes in its pre-ranking beta and its size. This allows some variation in security beta while avoiding the estimation errors that follow from using security betas directly (Fama and MacBeth, 1973; Fama and French, 1992). The cross-sectional Fama-MacBeth regressions are run for all securities with sufficient data for each month, using security specific values of ME and BE/ME, for which there is no error in the estimates. By rolling the regressions monthly, a total of 180 regressions per market are performed with an average of 344 securities per regression. The Fama-MacBeth coefficients are calculated as the time-series averages of the cross-sectional regressions, and the standard errors are calculated as in Equation 14.

4.2.4 Criterions for answering the research question

The results of the Fama-MacBeth regressions are presented in tables, and the sign of the coefficients as well as their t-statistics are compared to the results of Fama and French (1992), Artavanis (2013) and Ang et al. (2006). Although the main purpose of the thesis is to test whether a downside beta better explains excess returns than the CAPM beta, the fact that a Fama and French (1992) analysis is performed on three different markets also allows the thesis to test the robustness of the resluts obtained by Fama and French (1992).

In short, if the coefficient for downside beta consistently has a larger t-statistic than the coefficient for the CAPM beta in the cross-sectional regressions including the additional risk factors $\log(ME)$ and $\log(BE/ME)$, the downside beta is deemed to better explain excess returns than the CAPM beta. Further, if the results of the analysis are similar to the results of Fama and French (1992) in the different markets, the Fama and French (1992) results are considered robust across markets and different time periods.

5 Results and Analysis

This chapter first presents summary statistics of the data. Thereafter, the results of the Fama-MacBeth regressions are presented and analyzed.

5.1 Summary statistics of the dataset and the portfolios

The size of the dataset changes for each year depending on delistings and the quality of the data, i.e. missing values. Table 1 shows the minimum, average and maximum number of securities used in the Fama-MacBeth regressions. It is apparent that both the number of stocks and the quality of the data are increasing with time. For instance, the book value of equity is not available for most stocks in the Bloomberg database prior to the year 2000, which is also why we limit our dataset from 1995 to 2014. Since we start our analysis with a pre-ranking period of five years, where we are only interested in returns, the absence of book value data until the year 2000 has no impact on the results.

Table 1: Sample sizes. Minimum, average and maximum number of securities used in the cross-sectional Fama-MacBeth regressions for the different markets.

	Frankfurt	London	Stockholm
Minimum	207	336	51
Average	363	364	165
Maximum	463	402	207

A description of the market performance in the different markets is shown in Table 2, including the value weighted dividend adjusted returns of the sample securities and the equal weighted returns of the securities in the sample. The equal weighted index is calculated as the arithmetic mean of the returns of the securities without missing data in the dataset, it is not used in the regressions but will be commented upon in the discussion below.

Table 2: The market performance. Value weighted and equal weighted return index for the different markets and the average number of securities used to calculate the indices.

	Frankfurt	London	Stockholm
Value weighted	0.55	0.48	0.62
Equal weighted	-1.10	0.02	-0.17
Average stocks in index	513	460	241

The size and beta sorted portfolios' average excess returns for the entire sample period excluding the initial pre-ranking period are presented in Table 3, Table 4 and Table 5 for the Frankfurt, London and Stockholm stock exchanges, respectively. The smallest stocks with the lowest betas are found in the Northwest corner and the largest stocks with the highest betas are in the Southeast corner, this logic applies to all tables in the remainder of this sub-chapter.

Table 3: Portfolio returns – Frankfurt. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	-1.00	-0.46	-1.36	-1.49	-1.27	-1.75	-3.59
ME_2	-1.26	-1.39	-0.30	-0.57	-0.52	-0.50	-2.00
ME_3	-0.15	-0.42	0.56	0.02	-0.44	0.53	-0.07
ME_4	-0.16	-0.45	-0.23	0.45	-0.39	0.57	-0.78
ME_5	0.12	-0.13	0.25	0.45	0.83	0.52	-1.54
ME_6	0.39	0.51	0.73	0.47	-0.19	0.50	-0.48
Large ME_7	0.31	0.11	0.61	0.06	-0.37	-0.09	0.04

Table 4: Portfolio returns – London. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	0.15	0.36	0.78	0.44	-0.02	0.26	0.37
ME_2	0.54	0.50	0.36	0.01	-0.35	-0.79	-0.14
ME_3	0.38	0.13	-0.14	-0.16	0.14	-0.50	-0.43
ME_4	-0.14	0.19	0.36	0.73	0.03	-0.29	0.06
ME_5	0.15	0.13	0.22	0.39	-0.20	0.02	-0.48
ME_6	0.22	0.14	0.84	0.17	-0.14	-0.16	0.12
Large ME_7	0.42	0.66	-0.11	-0.23	-0.21	0.20	0.06

Table 5: Portfolio returns – Stockholm. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	-0.18	0.13	1.15	-0.33	0.57	-0.87	-2.41
ME_2	0.81	1.01	0.40	-0.16	-0.45	-1.01	-1.18
ME_3	-0.16	-0.26	1.02	-0.31	0.69	-0.11	0.37
ME_4	0.74	-0.11	0.63	-1.09	-0.78	-1.69	-0.92
ME_5	1.00	1.26	-0.05	0.87	0.18	-0.61	1.06
ME_6	1.12	1.07	0.38	0.59	1.08	0.68	-0.33
Large ME_7	0.07	0.46	0.62	0.32	0.71	0.24	0.03

As can be seen from Table 3 and Table 5, there seems to be a positive relation between size and excess returns in Sweden and Germany, while Table 4 shows the opposite relationship for the UK. The relationship between beta and excess returns is not as easily seen in the tables, although a larger beta certainly does not seem to be correlated with higher returns, as was found by Fama and French (1992). When comparing Table 3-5 to the equivalent table by Fama and French (1992) for stocks on the NYSE, AMEX and Nasdaq in the time period of 1963 to 1990, there is a striking difference in the clarity of the patterns. The table in Fama and French (1992) shows a perfect pattern of increasing returns for decreasing size, whereas the existence of such a pattern is hard to see at a first glance in our tables describing Frankfurt and Stockholm, and the opposite relation seems to hold for London. Both in Fama and French (1992) and in our study, the relationship between beta and returns is not obvious from looking at the tables above.

Table 6-8 presents the portfolio betas of the size pre-ranking beta sorted portfolios. In general, the portfolio betas increase with pre-ranking beta, which indicates a rather good persistency in the beta values. In the equivalent table of Fama and French (1992), the pattern with regard to pre-ranking betas is similar to ours. Further, Fama and French (1992) find an almost uncanny pattern of decreasing beta with increasing size. In fact, this pattern is much clearer than the pattern we find between pre-ranking beta and post-ranking portfolio beta. In comparison to the size − beta pattern observed in Fama and French (1992), our results resemble a random walk.

For the London stock exchange it is hard to identify any pattern at all, but it seems like the medium sized firms are the ones with the highest betas. In both London and Frankfurt, the range of the beta values increases with firm size, where the low betas tend to get lower and the high betas grow higher. The range effect is not observed in Stockholm.

The beta values, in general, are lower in Frankfurt than in the other observed markets, while London clearly has the highest values. Size-wise, the data for the Stockholm stock exchange is most similar to the results in Fama and French (1992). Interestingly, almost all beta values in Frankfurt are below one (average 0.72), whereas almost all are above one in London (average 1.34). This is explained by the bottom row of the two tables, where the very largest firms have low (high) betas in London (Frankfurt) and thus have a larger impact on a value-weighted index and therefore balance the equation. In Stockholm, the beta values are more balanced (average 0.93). However, it should be noted that the average portfolio beta values mentioned above are calculated as the arithmetic mean of the portfolio betas. If value weighted betas are used instead, the average betas in Frankfurt are 1.10, in London 1.14 and in Stockholm 1.02. One would expect the value weighted average of the betas to equal one. The observed discrepancy is explained by the fact that the stocks used in the regressions are not exact replicas of the stocks used to construct the indices, due to missing data.

Table 6: Portfolio betas – Frankfurt. Estimated betas for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	0.37	0.51	0.59	0.90	0.69	0.65	0.31
ME_2	0.42	0.44	0.53	0.53	0.61	0.85	0.76
ME_3	0.30	0.54	0.75	0.62	0.63	0.85	0.75
ME_4	0.44	0.46	0.64	0.51	0.62	0.77	1.22
ME_5	0.30	0.46	0.58	0.66	0.83	0.89	1.31
ME_6	0.25	0.42	0.61	0.80	0.91	1.16	1.41
Large ME_7	0.46	0.72	0.70	1.09	1.30	1.47	1.51

Table 7: Portfolio betas – London. Estimated betas for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	1.11	1.18	1.44	1.12	1.47	1.58	1.74
ME_2	1.03	1.02	1.40	1.47	1.51	1.75	1.83
ME_3	0.93	0.90	1.45	1.26	1.37	1.67	2.10
ME_4	0.90	1.09	1.23	1.47	1.57	1.49	2.02
ME_5	1.27	0.96	1.24	1.43	1.45	1.65	2.02
ME_6	0.58	1.06	1.03	1.32	1.41	1.75	1.95
Large ME_7	0.53	0.66	0.72	1.18	1.38	1.49	1.64

Table 8: Portfolio betas – Stockholm. Estimated betas for equal weighted double sorted portfolios sorted on size and pre-ranking betas.

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small ME_1	0.67	0.78	0.88	0.78	0.60	1.14	1.38
ME_2	0.62	0.67	0.77	0.56	0.70	1.12	1.00
ME_3	0.77	0.57	0.79	1.03	0.97	1.18	1.46
ME_4	0.63	0.75	0.83	0.91	1.10	1.42	1.65
ME_5	0.63	0.73	0.80	0.82	0.89	1.27	1.52
ME_6	0.60	0.69	0.80	0.76	0.88	0.97	1.18
Large ME_7	0.79	0.90	0.98	0.86	1.03	1.08	1.55

The equivalents of Table 3-5 sorted on ME and downside beta, BE/ME and CAPM beta and BE/ME and downside beta are found in Appendix A, Appendix B and Appendix C, respectively. These tables show similar, but less obvious patterns than the size and pre-ranking CAPM beta sorted portfolios.

5.2 The Fama-MacBeth regressions

The averages of the coefficients in the monthly Fama-MacBeth regressions, along with their t-statistics according to Equation 14, are presented in Table 9. In line with Fama and French (1992), the regressions generate negative coefficients for the betas, both for the CAPM betas and the Hogan-Warren downside betas. About half of our results, show that the coefficients for the betas are statistically significant at the 5 % level, whereas Fama and French (1992) do not find any significance.

When regressing excess returns on beta and $\log(ME)$ alone, we find that a stock on the Frankfurt stock exchange is rewarded with 0.23 % larger monthly excess returns when $\log(ME)$ is increased by one. A slightly lower effect is seen in Stockholm (0.16 %), whereas in London an increase in $\log(ME)$ by one decreases excess monthly returns by 0.04 %, although not statistically significant. Thus, as was expected from observing Table 3, Table 4 and Table 5, the effect of size is different in the different markets, and the results in Stockholm and Frankfurt are opposites to those found by Fama and French (1992). The book-to-market ratio has no significant effect on the excess returns in Frankfurt, whereas in Stockholm and London the $\log(BE/ME)$ coefficient is positive and statistically significant at the 5 % level, yielding an additional 0.4 % to 0.5 % excess return per month and unit. When using the downside beta in the regressions rather than the CAPM beta, the results change somewhat, although the signs of all coefficients remain the same.

When running the Fama-MacBeth regressions including both $\log(ME)$ and $\log(BE/ME)$, the results differ strongly between the different markets. The coefficients for both the CAPM beta and the downside beta are statistically insignificant in Frankfurt and London, which is in line with the results of Fama and French (1992). However the coefficients of both the CAPM beta and the downside beta in Stockholm are negative and statistically significant at the 5 % level.

The differences in the statistical significance of the CAPM betas and the downside betas are negligible and, for instance, in London the downside be-

Table 9: Results of the Fama-MacBeth regressions. After a beta preranking period of five years, a total of 180 cross-sectional regressions, one for each month in 2000-2014 are run, and then the time-series averages of the coefficients.The t-statistics are calculated according to equation 14 and presented in the parenthesis. The cross-sectional regressions are run on 49 size-beta double sorted portfolios. The portfolios are re-sorted yearly, which allows variation in beta-estimates of the individual securities. Data for market value of equity and book-to-market value is taken at the firm specific level. The regression coefficients are expressed in percent.

	β	β^-	$\log(ME)$	$\log(BE/ME)$
Frankfurt	-0.64 (-1.36)		0.23 (3.56)	
	-0.11 (-0.23)			-0.29 (-1.87)
	-0.60 (-1.26)		0.25 (5.25)	-0.01 (-0.04)
		-0.43 (-1.21)	0.24 (3.63)	
		-0.17 (-0.47)		-0.31 (-2.02)
		-0.43 (-1.19)	0.26 (5.25)	0.02 (0.12)
London	-0.46 (-1.36)		-0.04 (-0.75)	
	-0.80 (-2.38)			0.52 (3.44)
	-0.50 (-1.61)		0.01 (0.20)	0.33 (2.24)
		-0.43 (-1.45)	-0.01 (-0.12)	
		-0.68 (-2.38)		0.40 (2.68)
		-0.47 (-1.72)	0.05 (0.90)	0.35 (2.33)
Stockholm	-2.27 (-3.39)		0.16 (2.57)	
	-1.87 (-2.49)			0.42 (2.67)
	-1.70 (-2.58)		0.19 (2.71)	0.52 (2.98)
		-1.33 (-2.66)	0.20 (3.03)	
		-1.20 (-2.33)		0.39 (2.42)
		-1.16 (-2.58)	0.25 (3.28)	0.59 (3.20)

tas are on average slightly more significant than the CAPM betas, whereas the opposite holds for Frankfurt and Stockholm. The fact that there hardly is any difference between the two beta measures is a strong contradiction to the findings of Artavanis (2013), who finds that the CAPM beta is statistically insignificant in the presence of $\log(ME)$ and $\log(BE/ME)$, whereas the downside beta is highly statistically significant. In Sweden, the coefficients for both $\log(BE/ME)$ and $\log(ME)$ are positive and statistically significant at the 5 % level. In Frankfurt, the $\log(BE/ME)$ coefficient is completely subsumed by the positive $\log(ME)$ coefficient, whereas the opposite is true for London, where there is a statistically significant positive relation between $\log(BE/ME)$ and excess returns and $\log(ME)$ adds nothing to the explanation of excess returns. The results of the regressions with both $\log(ME)$ and $\log(BE/ME)$ as explanatory variables differ from the results in Fama and French (1992), who find a hihgly significant relation between both of the variables and excess returns.

5.3 Analysis and discussion

The research question of this thesis is to test whether a downside beta better explains cross-sectional excess returns than the CAPM beta. By applying the Fama and French (1992) test to three different markets, we test the results of Artavanis (2013) and Ang et al. (2006) who find a stronger relation between excess returns and downside beta than between excess returns and the CAPM beta. Artavanis (2013) also finds that while the CAPM beta is subsumed in the presence of size and a proxy for the book-to-market value, the Hogan-Warren downside beta remains strongly statistically significant in the Fama-MacBeth regressions. The findings of Artavanis (2013) and the appealing logic behind the Hogan-Warrren downside beta were what initially sparked our interest in the topic. As Markowtiz (1959) mentioned, variance as a risk measure is the most commonly used due to its ease of computation and its familiarity, although an analysis based on semi-covariance tends to give better portfolios than one based on covariance. By testing the conclusion of Artavanis (2013) on several markets we hoped to strengthen the case for the downside beta and increase the familiarity of a semi-covariance based analysis.

However, the results of our analysis differed from those that we expected and hoped for. While both Artavanis (2013) and Ang et al. (2006) find highly statistically significant positive coefficients for the downside beta (Ang et al. (2006) even find a t-statistic of 8), our downside betas (and CAPM betas) all had negative coefficients in the Fama-MacBeth regressions. By comparing Table 9 to the findings of Artavanis (2013), our result is a much less convincing case for the downside beta. In Table 9, there is hardly any difference between neither the size of nor the statistical significance of the different beta measures. This inconsistency with the results of other authors working with downside betas caused confusion about our results, which led to extensive robustness tests of our analysis. For example, although only monthly returns are presented in this thesis, we also did the analysis using daily data according to the process described by Ang et al. (2006), which yielded similar results as when using monthly data (not shown).

Howton and Peterson (1998) test the CAPM model with Fama-MacBeth regressions on US data from 1977 to 1993, although using a dual beta model developed by Bhardwaj and Brooks (1993). They find that a beta value calculated during months with market returns below the average market return is statistically significantly negatively related to excess returns in down markets, whereas the opposite holds in up markets for beta values calculated in months with market excess returns above their average. PSM (2002) come to similar conclusions in a very similar test. These results are logical, and follow from the specification of the Fama and MacBeth (1973) regressions, where the coefficient of beta in the Fama-MacBeth regression with beta as the only explanatory variable should be the market return. Thus, by dividing the sample into two sub-samples with only positive (negative) market excess returns, it should by definition be that the coefficient for beta in the Fama-MacBeth regressions is large and positive (negative). The CAPM beta explains how a particular stock follows the market index, thus by conditioning on the market returns, it should be no surprise that the CAPM beta has very high explanatory power in the tests of PSM (2002) and Howton and Peterson (1998), where the sample is divided according to up and down markets.

We perform a simple test to mimic the procedure by PSM (2002) on our dataset by simply changing the sign on all observations of the market return and the stock returns for observations when the market return is negative and perform our analysis on this modified dataset. This data snooping procedure yields a beta coefficient of 0.0305 with a t-statistic of 8.03 for Frankfurt, similar to the results of Ang et al. (2006). Although this weakness of the test explains the results of Howton and Peterson (1998) and PSM (2002), the strong results of Artavanis (2013) and Ang et al. (2006) are left unexplained by this nuance.

By failing to reproduce the results of Artavanis (2013), and not finding any significant difference between the CAPM beta and the downside beta, our results is a blow to the downside beta advocates, and yet more proof that there is no such thing as a free lunch. It seems unlikely that an investor who uses a downside beta based investing approach will achieve returns in excess of the market consistently.

In addition to testing whether the downside beta is a superior risk measure to the CAPM beta, our analysis can also be used to draw inferences from the Fama and French (1992) test. By applying the same test to three different markets, we find different results. While Fama and French (1992) find that smaller firms outperform larger ones, the opposite holds for our findings in Frankfurt and Stockholm, but not in London. This discrepancy is proof that the results in Fama and French (1992) are not robust across different times and markets, and the explanation for the difference in our results is likely explained by the market performance in the testing period. We run our Fama-MacBeth regressions in the years 2000-2014. During that period, two large crises have struck the market economy, both the burst of the IT bubble in the beginning of the century, and the more recent 2007-2008 financial crisis.

In Table 2, the equal weighted index of Frankfurt and Stockholm performed much worse than the value weighted one, while the difference was smaller in London. We hypothesize that the explanation for this is that in both Sweden and Germany, there were many small firms that went bankrupt or saw large declines in their market value during the burst of the IT bubble, which could explain why smaller firms perform worse than larger firms in these markets.

The fact that we do not consistently find similar results in the different markets is not necessarily proof that the cross-sectional Fama and French (1992) testing methodology is inappropriate. However, it shows that the conclusions of Fama and French (1992) are not general, but change in different times and markets. A first observation on the methodology is that it is sensitive to the performance of the market during the testing period. When regressing excess returns on beta, the resulting coefficient is almost entirely explained by the market return throughout the estimation period (remember the t-statistic of 8 that we got in the data snooping test explained above). Thus, to test whether beta explains cross-sectional excess returns, one must not investigate a time period where the market returns are close to zero. Further, as was discussed above, the difference between a value weighted index and an equal weighted index can be used to explain the relation between excess returns and market capitalization much more easily than by using Fama-MacBeth regressions, although on an entirely ex-post basis. Our observations are also confirmed by Howton and Peterson (1998), who conclude that the results in the cross-sectional regressions are market and time sensitive.

6 Conclusion

The validity of the influential CAPM model has been discussed and analyzed since its birth in the 1960s. One of the most common techniques to test the proposition that the CAPM beta is the only necessary explanatory factor for excess returns is to use cross-sectional Fama and MacBeth (1973) regressions. In a famous article, Fama and French (1992) add the explanatory variables $\log(ME)$, $\log(BE/ME)$, E/P and leverage to the Fama-MacBeth regressions and find that in the presence of $\log(ME)$ and $\log(BE/ME)$, the CAPM beta does not explain excess returns with any statistical significance. Some authors have used a conditional beta and a downside beta in the CAPM model, and tests have shown that these alternative risk measures survive even in Fama and French (1992) regressions (Ang et al. 2006; Artavanis, 2013; PSM, 2002; Howton and Peterson, 1998).

We perform a robustness test of the findings regarding downside betas of Artavanis (2013) and Ang et al. (2006) by performing Fama and French (1992) regressions on monthly stock returns on the stock exchanges in Frankfurt, London and Stockholm in the time period of 2000-2014. In essence, we find no difference between the CAPM beta and the (Hogan-Warren) downside beta in their ability to explain excess returns, a clear contradiction to in particular the results of Artavanis (2013). Thus, information of a downside beta parameter cannot consistently be used to achieve abnormal excess returns.

Additionally, by applying a Fama and French (1992) test on three different markets, we find that the results of the test differ across different markets. This adds to the observation of Howton and Peterson (1998), who find that the Fama and French (1992) results are not robust across different times. In particular, the market performance during the test period explains much of the effect of the CAPM beta, which from our standpoint is a weakness of the methodology.

Further research could focus on the development of new tests of the relation between beta and excess returns that are not as sensitive to the market performance as the Fama and French (1992) test, which could strengthen the intuition and understanding of the beta measure as a risk factor.

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A Portfolio returns sorted on size and downside beta

Table 10: Portfolio returns – Frankfurt. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	High β_7^-
Small ME_1	-1.78	-0.25	-0.75	-1.50	-1.20	-2.89	-2.57
ME_2	-1.68	-0.70	0.20	-0.74	-0.78	-0.54	-1.74
ME_3	-0.25	-0.32	-0.16	0.03	0.15	0.84	-0.43
ME_4	-0.71	0.04	0.04	0.10	-0.05	0.64	-1.05
ME_5	0.05	0.12	0.08	0.34	1.00	0.05	-0.97
ME_6	0.32	0.57	0.41	0.10	0.60	0.46	-0.53
Large ME_7	0.19	0.32	0.14	0.33	-0.30	-0.01	-0.04

Table 11: Portfolio returns – London. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	High β_7^-
Small ME_1	0.45	-0.02	0.87	0.61	0.21	0.12	0.12
ME_2	0.65	0.06	0.79	-0.31	-0.27	-0.38	-0.41
ME_3	0.19	0.27	-0.13	-0.21	-0.17	0.08	-0.59
ME_4	0.32	-0.23	0.04	0.65	0.26	-0.33	0.18
ME_5	0.04	0.45	-0.11	0.26	-0.90	0.14	-0.52
ME_6	0.34	0.26	0.41	0.09	-0.17	0.11	0.13
Large ME_7	0.30	0.24	0.18	0.06	-0.13	-0.28	0.41

Table 12: Portfolio returns – Stockholm. Monthly returns in percent for equal weighted double sorted portfolios sorted on size and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	High β_7^-
Small ME_1	-0.24	-0.07	0.71	-0.55	0.77	-1.82	-1.15
ME_2	0.86	0.85	-0.58	0.35	0.69	-1.74	-0.92
ME_3	-0.12	0.68	-0.12	0.29	0.18	0.18	0.28
ME_4	0.03	0.87	-0.09	0.04	-1.79	-0.38	-1.31
ME_5	1.15	0.61	0.47	0.90	-0.30	0.08	-1.30
ME_6	0.61	0.83	0.55	0.28	1.32	1.26	-0.29
Large ME_7	0.24	0.31	0.09	0.77	0.61	0.40	0.00

B Portfolio returns sorted on BE/ME and CAPM beta

Table 13: Portfolio returns – Frankfurt. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking betas

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small BE/ME_1	-0.82	-0.07	0.28	0.46	-1.58	0.24	-1.03
BE/ME_2	-0.15	0.11	-0.22	-0.12	0.02	-0.95	-0.52
BE/ME_3	-0.69	0.39	0.51	0.70	0.53	0.61	-1.04
BE/ME_4	-0.25	0.34	0.72	0.39	0.27	-0.30	-0.58
BE/ME_5	0.16	-0.65	0.72	0.62	0.59	0.13	-0.11
BE/ME_6	-0.24	0.71	-0.80	-0.58	-1.53	0.60	-0.60
Large BE/ME_7	-1.00	-1.50	-1.43	-0.79	-1.09	-2.83	-3.00

Table 14: Portfolio returns – London. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking betas

	Low β_1	β_2	β_3	β_4	β_5	β_6	High β_7
Small BE/ME_1	-0.30	-0.23	0.44	-0.05	-0.75	-1.59	-1.44
BE/ME_2	0.15	0.21	-0.24	0.47	-0.57	0.02	-0.57
BE/ME_3	0.05	0.35	0.54	0.25	0.37	0.00	0.33
BE/ME_4	0.51	-0.05	0.52	0.56	0.60	-0.65	-0.13
BE/ME_5	0.43	0.23	0.53	0.27	0.09	0.35	-0.20
BE/ME_6	0.01	-0.10	0.24	0.47	0.38	0.15	-0.03
Large BE/ME_7	0.46	1.48	0.34	0.26	0.28	-0.16	0.12

Table 15: Portfolio returns – Stockholm. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking betas

	Low β_1	β_2	β_3	β_4	High β_5
Small BE/ME_1	0.08	0.16	-1.27	-1.15	-1.48
BE/ME_2	0.93	0.32	0.26	-0.26	-0.79
BE/ME_3	0.54	0.64	0.88	0.52	-0.13
BE/ME_4	0.70	0.69	0.26	-0.05	-0.47
Large BE/ME_5	0.69	0.56	1.10	0.05	-0.55

C Portfolio returns sorted on BE/ME and downside beta

Table 16: Portfolio returns – Frankfurt. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	High β_7^-
Small BE/ME_1	-1.23	0.40	0.22	-0.28	0.10	-0.01	-1.56
BE/ME_2	-0.58	0.44	-0.09	-0.14	-0.09	0.08	-1.51
BE/ME_3	-0.54	-0.28	0.38	0.53	0.60	0.56	-0.44
BE/ME_4	-0.16	0.35	0.41	0.52	-0.11	-0.12	-0.30
BE/ME_5	0.06	0.48	-0.24	0.91	0.68	0.19	-0.54
BE/ME_6	-0.14	-0.08	-0.23	-0.82	-0.15	-0.62	-0.24
Large BE/ME_7	-1.82	-1.17	-0.88	-1.85	-1.17	-2.34	-2.37

Table 17: Portfolio returns – London. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	High β_7^-
Small BE/ME_1	-0.15	0.18	-0.34	-0.38	-0.83	-0.94	-1.48
BE/ME_2	0.44	-0.50	0.09	0.17	-0.17	0.20	0.75
BE/ME_3	0.13	0.27	-0.05	0.78	0.03	0.31	0.43
BE/ME_4	0.70	-0.10	0.52	0.20	0.28	-0.12	-0.17
BE/ME_5	0.18	0.32	0.96	0.36	-0.33	0.12	0.10
BE/ME_6	-0.14	0.11	0.16	0.71	-0.10	0.57	-0.19
Large BE/ME_7	0.79	1.36	0.37	0.08	-0.01	0.04	0.07

Table 18: Portfolio returns – Stockholm. Monthly returns in percent for equal weighted double sorted portfolios sorted on book-to-market value and pre-ranking Hogan-Warren downside betas

	Low β_1^-	β_2^-	β_3^-	β_4^-	High β_5^-
Small BE/ME_1	0.06	-0.24	-0.68	-1.06	-1.61
BE/ME_2	0.78	0.34	0.06	0.27	-0.95
BE/ME_3	0.52	0.57	0.63	0.65	0.04
BE/ME_4	0.75	0.42	0.16	0.63	-0.80
Large BE/ME_5	0.56	0.38	0.83	0.18	-0.31