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MASTER THESIS

Asset Pricing in Emerging Markets

Testing of Downside Risk Measures

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, May 2017

Tamara Ajrapetova
Signature

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Abstract

A review of vast literature base on Asset Pricing testing in advanced and emerging markets suggests that today no consensus has been reached on what is the right approach for dealing with the emerging market's specifics such as thin trading, market concentration and high volatility. This paper will consider a class of linear factor models, which are particularly famous due to the acknowledgement of Capital Asset Pricing Model (CAPM) and its subsequent modifications, which are the ultimate topic of this paper. Despite numerous research papers criticising traditional linear models and attempting to alter their embedded limitations, practitioners as well as academics return to already existing models such as the CAPM repeatedly. Anderson, Bollerslev, Diebold and Wu (2006), argue that the death of the model was over exaggerated. Firstly, because the model often works well despite its wrinkles and secondly more advanced multi-factor models that offer better statistical fit, lack the economic explanation of the variables and their interpretation in terms of systematic risk.

This opens a floor for discussion about the choice of asset pricing models, specifically should traditional CAPM model be applied or should alternative models such as D-CAPM be preferred. This paper offers statistical testing of traditional CAPM, Fama French CAPM and D-CAPM on a set of indices and portfolios with the use of GMM two-step simple and multiple regressions. Results has shown that on average downside beta tends to perform better in both emerging and developed markets than traditional beta. However, caution should be given to the use of systematic risk measures, as in case of emerging markets total risk measures such as semivariance and standard deviation can be preferable. Overall, unconditional models should not be a centre of discussion as many research papers along with this master thesis has shown that beta is non-constant over time, which confirms a general finding of non-constant volatility. The last chapter of this paper therefore looks at key conditional models.

JEL Classification G11, G12, G15, G31

Keywords Asset pricing, Capital Asset Pricing Models, Portfolio Theory, Factor Models, International Financial Markets

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List of Abbreviations:

APC – Arbitrage Pricing Theory

ARCH - Autoregressive conditional heteroskedasticity

CAPM – Capital Asset Pricing Model

C-CAPM – Conditional Capital Asset Pricing Model

CML – Capital Market Line

D-CAPM – Downside Capital Asset Pricing Model

DM – Developed Market

EM – Merging Markets

FF- Fama and French Factors

GARCH – Generalized Autoregressive conditional heteroskedasticity

GMM- General Method of Moments

IRR – Internal Rate of Return

MPT – Modern Portfolio Theory

MSB – Mean Semivariance Behaviour

MVB – Mean Variance Behaviour

OLS – Ordinary Least Squares

SML – Security Markets Line

WACC – Weighted Average Cost of Capital

1 Introduction

Asset pricing is one of the most crucial fields in finance, as it allows not to only price securities, but also make decisions on investments and capital structures of the firms. It is therefore not surprising that this field received extensive attention in academic literature. However, despite vast base of research, academics and professionals still did not reach consensus when it comes to treatment of Emerging Markets. In the past 20 years, emerging markets gained extreme importance in international financial markets and have become one of the regions where new opportunities are found. With the GDP growth and productivity growth slowing down in the developed markets, emerging markets are commonly viewed as the place for positive future economic prospects. Moreover, liberalization of trade and free movement of capital have allowed financial institutions, companies and individual investors to add more assets from these markets to their portfolios. As the results of such shifts, the tools and methods used by the businesses, financial institutions as well as individual investors who are using emerging markets either as diversification tool or as a main stream of income, have to also be adjusted to reliably express all of the region specific factors.

Over the past four decades there is a stable trend of using the model suggested by William Sharpe (1964) and John Lintner (1965) – CAPM (Capital Asset Pricing Model). It is widely applied by professional from the developed economies for measuring cost of capital for firms as well as valuing stock and portfolios worldwide. CAPM is a very intuitive model in the way it builds a relationship between the risk and the expected returns. However, as any model its assumptions are limiting its application only to a certain spectrum of problems. The main question this paper will try to answer is connected to reliability and applicability of CAPM model to emerging market settings as well as developed markets. As an alternative to traditional CAPM model, this research paper will test downside risk measures, and more specifically D-CAPM. The testing will be performed on indices and portfolios to account for possible inefficiency in index composition. The testing will specifically look at testing for zero-intercept or Jensen's alpha and cross-sectional testing of traditional beta and downside beta with different combinations of extra factors.

The structure of this master thesis proceeds as follows. The first section of the paper outlines the foundations of the asset pricing and its importance. In the following chapters, empirical evidence for and against traditional CAPM model is discussed. The paper then focuses on recent developments of downside risk measures that serve as an alternative to the traditional Mean-Variance Behaviour models, and proceeds to further testing of these measures on indices and portfolios in advanced and emerging markets. As a conclusive section, potential future research areas are discussed.

2 Aims and Objectives

In the past 10 years, liberalization of trade and innovation in financial software lead to tighter ties between the emerging markets and the advanced economies. These trends has put into question the necessity of introducing alternative risk measures for the emerging markets. Despite, vast and growing body of literature on asset pricing, there has been a limited research focused on testing of the asset pricing models in the emerging markets. Consequently, resulting in no consensus about "the one model", which would be widely accepted as a standard model to use. Thus, the aim of this research paper is to investigate the current state of the equity markets in the emerging economies by testing several model conditions and test several widely acknowledged in DM models. This goal can be broken down to more trackable objectives and research questions that one can see in the table below.

Table 1 - Research Aims and Objectives

Objective	Research Task
Objective 1: Provide comprehensive overview of the key models in the area.	• Research differences between traditional and alternative approaches to asset pricing • Specify limitations of the current research • Highlight the gaps that exist for the future research
Objective 2: Offer comprehensive comparative analysis for two or more models	• Use frequency distribution analysis to estimate whether the returns are normally distributed • Through the use of simple linear regression analysis estimate if beta is stationary and alpha is zero. • Based on cross-sectional regression compare and contrast explanatory power of different risk variables.
Objective 3: Conclusions and Assessment of Results	• Provide summary of the key points evident from the analysis • Define key limitation of the results • Suggests possible areas of future research and improvement

3 Literature Review

3.1 Introduction to Asset Pricing Models

Asset pricing models are tools for individuals as well as for corporations in analysing and making asset/portfolio related decisions. In general, asset-pricing models deal with quite diverse set of financial concerns. Firstly, one of the most important purposes of asset pricing models is determination of asset-allocation or in other words, explanation of how individuals/corporations choose to construct their portfolios. This particularly implies how the weights are assigned to individual assets with a given portfolio. Secondly, all of the models under this umbrella term deal with explanation of the relationship between risk-return. They provide measurement schemes of financial risk associated with individual assets as well as with portfolios of assets.

These are not the only applications of asset-pricing models as they are also used for capital budgeting or investment appraisals where the parties, usually managers of the firm, are mainly concerned with proper estimation of internal rate of return (IRR) of a particular project through estimation of weighted average cost of capital (WACC). Moreover, linking to the above-mentioned asset pricing models also play a crucial role in defining the capital structure of the firm. This particularly implies the appropriate choice of weights in equity and debt combinations.

The modern approach to asset pricing starts from several very logical assumptions about the expectations of the investor/s. Firstly, and most importantly with the purchase of any financial asset the investor obtains the right to receive future cash flows of the asset. Equity markets are quite volatile and are dependent on various macroeconomic factors, thus the size of the payments are conditional on the performance of the specific company and market as a whole. As the result, no one can define the future cash flows with certainty. According to Munk (2013), risk-averse investors will give a higher value to a payment of certain size during the “bad” state rather than “good” state. This simple relationship is captured in the term “state price”, firstly introduced by Arrow (1953). The main argument is that state prices are the same for all assets in a given state. This is possible only if the investors are rational. Therefore, to price an asset the modern asset pricing theory models the states and related state prices (Munk, 2013).

Capital Asset Pricing Model (CAPM) is the most well known asset pricing models when it comes to practical application as well as academic reference. The model is based on Modern Portfolio Theory (from now on MPT) firstly introduced by Markowitz (1952) and is just a version of much older valuation technique – risk-premium model (Harrington, 1983). Risk-premium models are based on relationship where higher return is assigned to increasing levels of risk. This key idea remained in the CAPM as well as other models such as APT, however the difference lies in the way the risk is measured. The very way in which CAPM estimates risk, has caused a lot of discussion and extensive academic research. To be able to assess the reliability of CAPM model one should start with the theory that lies behind it.

3.1.1 Mean-Variance Behaviour

When talking about measurement of risk, CAPM is one of the most intuitive ways of explaining the relationship between risk and return. It is based on the Efficient Market Portfolio theory suggested by Markowitz (1952) also called Modern Portfolio Theory, where the investors are assumed to be rational and risk-averse. Therefore, seeking to reduce the amount of risk given a certain level of return. MPT is the first model that explicitly deals with risk in portfolio settings (Harrington 1983, p. 11). The main claim of the model is related to allocation of the assets, particularly that it is better to choose assets not based on their individual characteristics, but rather based on the way they behave in a bundle with other assets in one's portfolio. This idea, of so-called diversification, plays a crucial role for the development of CAPM model and for financial risk management overall. Markowitz (1952) argued that it is possible to construct optimal portfolio that would give the highest return for a given level of risk that an investor would not be able to achieve given an individual asset. Rational investor will thus choose a combination of assets that will yield the highest return given a specific level of risk. This set of portfolios are called efficient and when plotted onto a graph are lying on the efficient frontier. The investor than chooses the portfolios based on his/her risk appetites, which are, represented by utility curves. The utility of the investor is defined by the variance and the mean returns of the portfolio, which express the trade-off between the risk and return. Such relationship is generally called *Mean-Variance Behaviour (MVB)*, and serves as the base for the development of CAPM.

The main limitation of MPT is its estimation complexity, which kept it from adaptation in the real world. Mainly, the model was difficult to apply when the number of assets within the portfolio increased. For a portfolio with N assets, the number of correlations that would have to be estimated grew to:

Equation 1- Estimation of Number of Correlations MPT

$$N\frac{(N-1)}{2}$$

As the result, if one would consider portfolio with more than 10 assets, the number of correlation estimations would exceed 45. At the time when the model was introduced, there was no such computation power that would be able perform such calculations. CAPM and other models that were inspired by the MPT aimed to simplify the model to make it more practical.

3.1.2 Development of CAPM

CAPM model takes its foundations from Markowitz MPT and thus shares the same market equilibrium conditions. The model inherited the assumption about the preference of holding portfolios of risky assets opposed to individual asset (diversification effect). Before CAPM was developed, Tobin (1958) extended Markowitz MPT to so-called Two-Fund Separation approach, where the optimal portfolio was constructed from risk-free security and portfolio of risky assets, this relationship can be graphically represented with Capital Market Line (CML).

Development of CAPM model was facilitated by Sharpe (1964), Treynor (1961) and extended by Lintner (1965), Mossin (1966), Fama (1968a, 1968b), and Long (1972) on independent basis with the use of the modification suggested by Tobin. The fundamental assumption of the model is that there is an increasing linear relationship between the expected risk the investor bears and the expected return. The risk-free asset compensates for the delayed consumption, that according to the Expected Utility Theory (EUT) is viewed by investors as undesired, and thus should be compensated for. The premium in turn is a compensation for bearing extra risk that cannot be diversified away. CAPM can be graphically represented by Security Market Line (SML), which uses beta as a measure of risk of the portfolio opposed to standard deviation used in CML.

Before moving on into discussion about empirical testing of CAPM, it is crucial to define what are its key assumptions. In this paper, the focus will mainly lie on those that will be tested in later chapters. Most of the assumption that shape the model are coming from its predecessors MPT and EUT. Firstly, the model assumes that one period returns are normally distributed and or belong to any other type of two-parameter symmetric distribution (Fama and MacBeth 1973, p. 607). This assumption comes from MVB and is mandatory condition for deriving efficient frontier under MVB (Abbas, Ayub and Saeed, 2011). This condition is directly related to another important assumption that investors are risk-averse and choose their portfolios based on the maximum expected utility theory. Thus, the optimal portfolio for any investor should yield the highest return for a given level of risk. Testable conditions can be summarised as follows:

- Normality condition given by the Mean-Variance Behaviour.
- Relationship between expected returns of any security or efficient portfolio and its risk measure is linear.
- Beta is the only measure for the security/portfolio, thus no other majors can systematically explain the expected returns.
- Given that investors are risk-averse, the securities with higher risk should always provide higher expected return.

3.2 CAPM Empirical Evidence

There is quite extensive body of literature that deals with testing of CAPM model especially in the Developed Markets (from now DMs). The first tests were performed in early seventies. During this time, the model was gaining its popularity and much of the research done offered evidence in favour of CAPM theory. The most influential studies of that time include Black, Jensen and Scholes (1972), Fama and MacBeth (1973) and Blume and Friend (1973). The study of Fama and MacBeth was performed on NYSE stocks. The study concludes that the risk-return regressions are consistent with the efficient capital market and two-parameter portfolio model hypotheses. The testing done by Black, Jensen and Scholes (1972) was also performed on NYSE stocks, however included a different set of tests, the key findings of the research postulate that there is a positive relationship between average returns and market beta. However, when performing time series regression tests the coefficient of the intercept is non-zero and beta is found to be non-stationary and unproportioned to the excess returns. Thus, putting forward new violations of CAPM.

The success of CAPM during seventies has quickly eroded as more research was done. One can identify several perspectives on problematics of CAPM in the literature. The first perspective that is important to mention relates to rejection of CAPM as of a reasonable model. Ross (1977) and Roll (1977), argued that CAPM does not hold when indices are used for calculation of returns of the market portfolio. They claimed that there is an evidence that indices are not efficient portfolios and thus exhibit deviations from efficiency that can bias the risk and return relationship. Consequently, since the true market portfolio is unobservable the CAPM model cannot be empirically used. Many though did not support this perspective, as the only alternative in a form of Arbitrage Pricing Theory has not proven its reliability in testing.

The second perspective, expresses greater loyalty to the fundamentals of the CAPM model, however admits that there are certain anomalies that require necessary adjustments. The most common adjustments under this perspective are additional factors that created a new notion of so-called multifactor CAPM. Fama and French (1992) published the most influential paper under this classification. Opposed to traditional CAPM their findings have shown that beta is not the only measure of risk. Furthermore, size (Market Equity) and value (Book-to-Market ratio) effects outperformed beta in explanatory power of excess returns. Based on their findings small size firms on average tended to receive higher returns than predicted by their betas, whereas firms with large market capitalization on average received lower returns given their betas. The same applied to value stocks (stocks with high book-to-market equity ratios), that tended to receive higher returns than their beta would predict. These findings supported previous findings of Black, Jensen and Scholes (1972), Miller and Scholes (1972) and were further confirmed by research done by Reinganum (1981), Banz (1985), Stattman (1980) etc. However, the paper also received criticism from the side of Black (1993) who claimed that Fama and French (1992) results are fostered by data mining and are not properly explained. Despite, this criticism, the model is still widely used and is considered to be more reliable alternative to the CAPM. Other studies in this area suggested extension of3-Factor Model through additional of more factors such as: (1) momentum, (2) time effects, (3) P/E ratio.

These were not the only anomalies that were discussed during eighties. Another large area of testing was connected to efficient market hypothesis and anomalies that had to do with the capital markets efficiency. Rozeff and Kinney (1976) reported January-effect, other effect included weekend effect and leverage effects. Other important researches included papers published in the Emerging Markets, Iqbal and Brooks (2007) have studied the role of thin trading adjustment for beta calculations. The findings suggest that correction for thin trading does not affect the results of asset pricing. Other studies also include Cheung and Wong (1992) and Ahmad and Zaman (2000) that study Hong Kong and Karachi

Stock exchanges. Despite, some research being done in the EMs there is no consensus on if CAPM is rejected within EM context.

The last perspective, and the one supported by this research paper is attempting to fix theoretical flows of the CAPM model. In this case we no longer talk about multifactor CAPM, but rather modified-CAPM (Abbas, Ayub, Sargana and Saeed 2011, p. 192). Under this classification, academicians were trying to address issues such as non-zero intercept, asymmetric distribution of returns (normality) or CAPM without risk-free borrowing. One of the main findings was done by Black (1972) who suggested Zero Beta CAPM with unlimited short selling of risky assets, which accounted for the problem of efficient market portfolio previously outlined by Ross (1977) and Roll (1977).

Another important stream of research under this classification deals with the weaknesses of beta as a measure of risk. One of the problems highlighted in the research done by Black, Jensen and Scholes (1972) was that beta coefficient is time varying. These areas of research became more popular with research done by Engel (1982) who introduced ARCH and GARCH processes and which later were extended into time-varying conditional expected returns and variances (Stambaugh, 1987). A new Conditional CAPM (CCAPM) not only accounted for time-varying beta but also fixed for weaknesses of the efficient market hypothesis theory highlighted previously. The majority of the testing of CCAPM has proven its reliability (Lettau and Ludvigson 2001; Zhang 2003; etc.). There were however, certain factors that CCAPM was not able to account for, specifically the value effect, described by Fama and French (1993) and the momentum effect. Later, the model lost its popularity due to large alphas that indirectly violated its main assumptions.

Vast body of literature was developed on the issue of normality condition. Various researches has shown that asset returns are non-normally distributed and often exhibit skewness and kurtosis (Fama (1965); Kon (1984); Richardson and Smith (1993); Aparicio and Estrada (1997); Dufour, Khalaf and Beaulieu (2005) etc.). The majority of the investigation done on stock exchanges has shown all factors present in the emerging markets fat tails, high peaks and skewness. Adcock and Shutes (1998, 2002), Harvey and Siddique (2000) all highlight the importance of skewness in asset pricing. The first solution to this problem (Ingersoll (1975); Fang and Kai (1997); Harvey and Siddique (2000); Jurcenzko and Maillet (2002)) was to use higher moments. Christie-David and Chaudrhy (2001) show that third and fourth moment help to explain the returns in the futures markets better, whereas Harvey and Siddique (2000) take it further to negative co-skewness showing that skewness overall is not a negative attribute, what investors really dislike is negative co-skewness. Even though co-skewness is able to account for some aspects, it should not be confused with the downside risk, which captures the asymmetric movements. The breakthrough was reached through reassessment of the EUT and MVB.

Kahneman and Tversky (1979), Gul (1991) and Estrada (2000, 2002, and 2007) all conclude that investors do not give equal weights to downside and upward movements.

Estrada (2002) claims that investors in the emerging markets are more focused on downside risk. Brooks and Galagedera (1994, p.5) argue that given identical regulatory and tax environments the loss of the utility caused by the loss of 1 dollar is much higher than the utility of gaining one dollar, due to the different wealth context. Thus, the problem of the CAPM theory lies in the way it defines utility that investors receive from their consumption. Based on the MVB and CAPM model, marginal utility of receiving an extra dollar and losing extra dollar is the same; however, in the reality one can argue that this is not the case. Levy and Markowitz (1979) tried to defend the MVB framework, based on the notion that it yield utility approximately equal to the expected utility, however Estrada (2002) argues that the same conditions can apply for Mean-Semivariance Behaviour.

Based on the evidence, one can assert that both developed and emerging markets exhibit non-normality and preferences for downside risk, putting importance of downside risk measure to the core of asset pricing not only in developed economies but also in the emerging markets.

3.3 Downside Risk Measures

Downside risk measures have been neglected for long and started gaining their popularity just in the last 10 years and specifically after the crisis of 2007-2008, where the problem of asymmetric distributions were identified not only in asset pricing but also in credit risk. Currently, there are numerous measures such as semivariance, expected shortfall and recently introduced realised semivariance (Nielsen, Kinnebrock and Shephard, 2010) that are widely discussed in academic literature as alternatives to traditional tools.

The first influential work in this direction within asset pricing was written by Roy (1952), who argued that Safety-First Rule (from here after SF-rule) plays the key importance to the assessment of the risk of the portfolio. The main claim of his approach was based on the limitations of traditional Mean-Variance Behaviour, which assigned equal weights to downside and upside movements. Even though Markowitz (1959) did consider downside risk in his seminal book, highlighting that semivariance produces more efficient portfolios than the standard deviation. The decision was made towards the traditional risk measures due to computational complexity.

The first testing of downside risk measures focused on superiority of semivariance over standard variance. Quirk and Saposnik (1962), Mao (1970), Ang and Chua (1979) have shown that semivariance (both mean and target) exhibits explicit advantages over simple variance. However, at that time there was a limitation in the applicability of these findings as there was no method to quantify stochastic dominance, which was one of the main tools used to measure semivariance. The breakthrough has been achieved by Bawa (1975), who has generalized the semivariance risk measure in his Lower Partial Moment (LPM) theory. Later in 1977, Fishburn has extended this research to incorporate all of the investors – risk averse, risk seeking and risk neutral.

The most influential works related to modification of CAPM framework based on the SF-rule are Hogan and Warren (1974), Bawa and Lindenberg (1977), Harlow and Rao (1989) and Estrada (2002) and Estrada and Serra (2005). The main conclusions reached by all of the papers states that DCAPM is both theoretically and empirically superior to CAPM. Nevertheless, this does not nullify the importance of CAPM as it can be regarded as a specific version of DCAPM when the distribution is normal.

Despite, one key theme that all of this papers share, the downside risk definition varied from author to author. The first model suggested by Hogan and Warren (1974) called E-S model, suggested to use semideviation. Under this model, a security would add to the risk of a portfolio only if its returns fell below risk-free rate. Thus, the benchmark for calculation of downside movements was risk-free rate not the mean return. Bawa and Lindenberg (1977), who have generalized this approach in their Mean-Lower Partial Moment (MLPM) model has kept this definition of semideviation, whereas Harlow and Rao (1977) suggest replacing risk-free rate with any arbitrary benchmark return.

In the most current research, Estrada (2002) extended this idea to incorporating risk measure called downside beta with respect to mean returns or alternatively to any benchmark. In his recent papers (Estrada 2000, 2001, 2004b) he claims that opposed to previous measures, downside beta is a measure of systematic downside risk, which is equivalent to traditional beta and thus sustains its logic. In this research paper, will focus on testing of semideviation as suggested by Harlow and Rao (1977) and downside beta adopted by Estrada (2000).

3.4 Research in Emerging Markets

Despite, quite vast testing done in the developed markets, emerging markets do not possess much of empirical testing. The key studies that were undertaken in the emerging markets include papers of Estrada (2000, 2002), Estrada and Serra (2005) and more recent studies done for Pakistani equity market performed by Abbas, Ayub, Sargana and Saeed (2011). These studies take different approaches to testing of risk measures, some focus on testing on indices, with the aim of covering larger number of countries. Whereas, other give preferences to portfolio testing, within just one specific market. Despite the differences in the methodologies and data sets, all of the authors agree that DCAPM is superior risk model in the context of Emerging Market. Nevertheless, this has been empirically confirmed only for some of the markets, thus this might not hold for the others. Therefore, there is a gap in the literature that would perform proper testing, especially portfolio testing, for other emerging markets. Furthermore, as to the knowledge of the author, past papers did not include testing of Fama-French Three-Factor model with CAPM and DCAPM.

4 Research Hypotheses

Based on previous research and trends that have been outlined in the body of the past literature this section will derive a set of hypotheses. This research paper will have two sets of tests; therefore, the hypotheses will be outlined for each of the sections separately. These hypotheses can be referred to as sub-hypothesis that assure proper testing of the main hypothesis of this paper, which is connected to rejection of reliability of CAPM as a pricing/valuation model for the EM.

Grand Hypothesis Index and Portfolios Testing: CAPM will not able to differentiate the cross-section of equity returns in the emerging markets, whereas downside risk measures will prove their superiority.

The construction of sub-hypothesis was based on the limitations of CAPM. Hypothesis 1 looks at the first condition of the traditional CAPM model, which is rooted in its predecessor MPT. According to CAPM, the utility of the investor is represented by quadratic utility, which implies normal and symmetric distribution for determination of efficient frontier (Abbas, Ayub and Saeed, 2011). Following this assumption, the whole distribution of the returns can be characterized by the first two moments; mean and variance. Based on previous empirical research in the advanced economies, the author assumes that this assumption is quite limiting and EM will exhibit fat tails, skewness and asymmetricity in their returns.

H1: The return distribution in the emerging markets will exhibit asymmetricity and fat left tails.

This hypothesis will be tested for both of indices and portfolios.

4.1 Hypotheses Part I

The first set of hypothesis will be related to testing of the four risk measures (based on Estrada 2004) on the index returns. One of the main aims in this section would be to show that the downside risk measures have higher explanatory power than their traditional counterparts do.

I-H1: Downside risk measures should show higher explanatory power than traditional risk measures.

The next hypothesis will be associated with Beta coefficient, according to some of the previous research such as the one done by Harvey (1995), the mean returns do not have any correlation with beta and the R-squared coefficient is zero. This study was performed on advanced economies, thus the author finds logical to assume that similar conclusions can be reached in emerging markets

I-H2: Beta coefficient will have zero association with the mean returns, represented by coefficient of determination being close to zero.

4.2 Hypotheses Part II

In the previous section, we have outlined the key hypotheses for the testing of risk measures on indices. This kind of testing has its limitations. Thus, it makes sense to construct a separate set of hypotheses for the testing on portfolios. The first hypothesis in this section is related to testing of the Traditional CAPM with the Time Series test. According to previous research (Black, Jensen and Scholes 1972), the author thinks that the test will show non-zero alpha coefficients and non-stationary and non-constant beta coefficients.

II-H1: The alpha coefficients will be statistically different from zero, being negative for the high-risk portfolios (beta greater than 1) and positive for the low-risk portfolio (beta lower than 1).

If this hypothesis will prove to hold, the high-risk securities priced by CAPM would earn consistently less than the predicted amount and the low-risk securities would provide on average higher return.

Proceeding to further testing, based on previous research it is possible to assume that the variation in the excess returns that will be explained by the beta coefficient will be erased when the size effect will be removed. Thus, the author assumes that beta will not vary significantly from portfolio to portfolio. This contradicts one of the main conditions of CAPM model that beta is sufficient to describe the cross-section of returns and no other risk measure can systematically affect expected return (Fama and MacBeth 1973, p. 624).

II-H2: Beta coefficients will exhibit low explanatory power of the variations in the excess returns. The average returns for small firms with high value will be too high given their beta coefficients, whereas large size growth stocks will exhibit lower returns than predicted by their beta coefficients. This will cause flatness of the relationship. Furthermore, when controlling for size and value effects, beta will be insignificant.

Lastly, but not least importantly, this part of the paper stresses importance of downside risk measures, thus the author believes that D-CAPM, will outperform traditional CAPM model in the Emerging Marekts and will be able to serve as a substitution for more factor heavy models such as Three Factor Model.

II-H3: Downside beta will exhibit higher association with mean returns and as the result can serve as an attractive less complex alternative to both multifactor model and traditional CAPM model.

5 Methodology

This research paper will be sub-divided into two distinct parts. The first one will perform statistical significance analysis and analyse general development and characteristics of equity markets in the emerging economies. Whereas, the second part will be focused on performing more of an economic analysis based on portfolio testing. This part will require more extensive data collection and computations that are more technical, thus due to time constraint, it will contain analysis of only two markets - one from advanced economies (U.S.) and one from emerging markets (India). This paper is similar to previous literature, in the sense that it will attempt to test explanatory power of several risk variables in connection to cross-section of returns in EM. However, it contains unique combination of models, portfolio sets and time period under study.

This section is therefore structured in the following way: (1) discussion on data sources for both parts of the research; (2) methodology in which portfolios were constructed; (3) outline of the tools used to perform both types of analysis; (4) lastly but not least importantly limitations of current methodology will be specified.

5.1 Data and Variables Part I

As has been mentioned before this research paper will focus on emerging markets. Since aggregating the data for all of the countries falling under this category would be out of the resource of this project, it has been decided to pick several countries inside of the emerging market umbrella and compare them to the developed markets. The data collected on these markets would be of the form of stock indices that would represent the total market movements and associated with them returns.

Table 2-Emerging Markets Sample

Emerging Market	World Market
India	MSCI World Index
China	
Colombia	
Russian	
Czech	
South Korea	
Brazil	
Indonesia	
Mexico	
South Africa	
Pakistan	
Morocco	
Egypt	
Chile	
Argentina	
Turkey	

Thailand	
Poland	
Peru	
Jordan	
Israel	
Hungary	
Taiwan	
Sri Lanka	
Philippines	
Malaysia	

The author was seeking to choose countries that in the past 10-15 years were entering the international arena in terms of volumes of financial transaction. Thus, she was mainly interested in those countries where one can see increasing international activity and integration. The first choice has fallen on the BRIC countries. This acronym was firstly used by economist from Goldman Sachs, Jim O'Neill, who used it to refer to growth opportunities in Brazil, Russia, India and China. According to O'Neill these countries would account for large proportion of the world production (BRICS Ministry of External Relations, n.d.). The countries later on established official cooperation and BRIC has been extended to BRICS to include South Africa. However, to ensure that the sample is reliable representation of population it has been decided to extend this selection to other emerging countries that are less developed but in recent years are common places for Foreign Direct Investment of multinational companies. This paper will therefore cover 26 countries in total, the list of which one can see in Table 2.

To be able to make a comparison this paper will also perform the same kind of analysis on the developed markets. To ensure that the tests are statistically significant 23 countries will be taken into account (see Table 3).

Table 3 - Developed Economies Sample

Developed Markets	**World Market**
Austria	
Australia	
Belgium	
Denmark	
Finland	
France	
Germany	
Greece	
Hong Kong	
Ireland	**MSCI World Index**
Italy	

Japan	
Netherlands	
New Zealand	
Norway	
Canada	
Portugal	
Singapore	
Spain	
Sweden	
Switzerland	
UK	
USA	

For all of the countries MSCI, capitalization-weighted indices quoted in US dollars, were obtained from Thomson Reuters. The data was collected for the period starting from 01/01/2000 ending on 31/12/2016 for monthly movements and includes not only capital gains but also dividends. For this purposes MSCI offers two types of Total Return Indices (MSCI, 2015):

- Gross Dividends – reinvests the total amount of dividends distributed to persons residing in the country; however, it does not account for any tax credits.
- Net Dividends – reinvests dividends after the withholding tax, the tax rate is defined as the rate for non-residents who do not benefit from DTT (Double Tax Treaties).

In this paper, we will consider Gross Dividends model to make sure that we are not accounting for any tax and that all of the dividends are reinvested.

5.2 Data and Variables Part II

According to previous research Friend and Blume (1970), Black et al. (1972), Fama and MacBeth (1973), to improve precision of beta estimates through reduction of the measurement error term, the testing of asset pricing models should be undertaken on portfolios opposed to individual stocks or indices. The main aim behind construction of portfolios is to assemble them in such a way that would exhibit distinctive variation in excess returns or in other words show dispersion of risk coefficients. This approach also allows avoiding the problem of existence of outliers, which are quite common within emerging markets (Estrada and Serra, 2003). The classical approach to construction of such portfolios is to choose respective indices for the markets, take the stocks that constitute a part of them and rank them based on certain risk factor. The next step is to perform partitioning of the ranking based on some pre-set rule. For example, the first 10% of the stocks with the highest downside beta would constitute the first portfolio and the rest would be sub-divided in the same manner. Fama and French (1998) wrote one of the most well-known academic papers adopting such methodology. The formation of their portfolios was based on two factors, size and value. The main difficulty related to construction of such portfolios is connected to the necessary rebalancing, which in some cases is done as often as monthly.

As this research, paper will include testing of standard equilibrium model in representation of traditional CAPM and its modification D-CAPM, the author will apply the same methodology to construction of portfolios as in paper of Fama and French. Since the time of this project is limited to 3 months, proper collection and rebalancing of data would be difficult to perform. Thus, to prevent bias in construction of portfolio sets, portfolios constructed by French (2017) will be utilized. For the purposes of this research, 6 and 25 portfolios sorted based on Size and Value and 3-factors have been downloaded from French public data library for US and Asia Pacific (including Australia, Hong Kong, New Zealand and Singapore). However, this data library covers only developed markets.

For the emerging markets, similar portfolios were available only for Indian equity market. These portfolios are constructed and regularly updated by Agarwalla, Jacob & Varma (2017) in cooperation with Centre for Monitoring Indian Economy (CMIE). As to the knowledge of the researcher, they have not yet been used in testing of the models.

Overall, the gap in the data availability of factors of pricing models such as Fama and French Three Factor Model highlights the importance of further research within the scope of the EM, since application of these models is constrained by the accessibility and availability of these factors. This also stipulates importance of alternative models such as D-CAPM that can aid to avoid issues connected to maintenance and regular update of such data libraries.

5.2.1 Portfolio Construction

For the second part of the testing, the author will test 3 models, traditional CAPM, Fama-French Three Factor model and the downside risk D-CAPM model. The selection of the models was based on the previous literature. To avoid simplifications connected to the testing of indices the author decided to use portfolios constructed by French (2017) and similar portfolios constructed for the Indian market by Agarwalla, Jacob & Varma (2017). All of the portfolios are regularly updated. Therefore, the most recent data is readily available. The research in this section will look at the period commencing on 01/01/1993 and ending 01/01/2016, due to the restrictions posed by the Indian market data, however in case of testing for intercept the whole data set will be used for the US. In the following few paragraph, the construction off the portfolios will be discussed and compared.

One of the most important issues when it comes of reliability of the portfolios has to do with their coverage. The more firms the portfolios cover, the less selection bias they should exhibit. French (2017) portfolios for the US are formed every June for all of the stock that have available equity data for July of year t to June of t+1. The stock should be included into the following indices: (1) NYSE, (2) AMEX, and (3) NASDAQ. The portfolios are the result of the intersection of two portfolios formed on size (ME) and three portfolios based value or in other word the ration of book-equity to market equity (BE/ME).

Indian portfolio cover all of firms listed on Bombey Stock Exchange (BSE), which were covered by the Prowess database. During the period of 1991-2013 the database, include in total 7,082 firms (Agarwalla, Jacob & Varma 2014). However not all of the firms had valid price data and were liquid through the period. To account for these market characteristics, the authors has to introduce liquidity filter for years (1993-2000), when illiquid firms were traded on BSE. The portfolios include only the firms that traded more than 50 days within 12th month period, which implies at least one trade within a week. The construction of the portfolios is based on the same methodology as in case of Fama and French. One of the important difference that has to be highlighted is the way the size and value breakpoints were identified. Value breakpoints were estimated based on the same methodology; however, this does not apply to size breakpoints.

In case of the Fama and French (1993) the portfolios are ranked into small and big based on the median size of NYSE stocks, however one of the specifics of the Indian market is that it is dominated by a large number of small firms. Therefore, this strategy would result into disproportionate allocation. Alternative, approach suggested by Agarwalla, Jacob & Varma (2014), involves classifying big stocks as the top 10% by market capitalization and the rest is classified as small stocks. Another important difference is the formation date, opposed to forming portfolio in June, Indian portfolios are formed in March, per the fiscal year end which applies for approximately 89% of the firms.

Proceeding on it is important to define estimation of market premium and risk-free rate. The table below provides comprehensive summary of the indicators used for each of the factors:

Table 4 - Components Estimation

Components	US Portfolios/ Asia Pacific	Indian Portfolios
Rf	Treasury bill rate (from Ibbotson Associates)	91-days T-bill rate
Rm	Value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ etc.	Value-weighed portfolio of all of the stocks

For detailed explanation of calculation of returns and factor calculation, please refer to the original paper of Agarwalla, Jacob & Varma (2014) and French (2017) website.

5.3 Part I: Methods of Analysis and Models

The first part of this research paper, will examine the first and the last hypothesis (I-H1 and I-H2), which is connected test for normality of return distribution and comparison between the explanatory power of different risk measures. To start the testing the paper will take similar approach to Estrada (2002) and firstly look at the correlation of the returns between the EM markets and compare it to the correlation with the world market.

This will be done through correlation matrix. All of the calculations in this section will be performed with the use of Microsoft Excel and eViews.

The first hypothesis that will be tested in this section comes from the Markowitz's Mean-Variance behaviour and is connected to the distribution of the returns. If mean-variance behaviour holds then the distribution of the returns, as suggested by the model, should be fully explained by the first two moments (mean and the variance), as the result the distribution should be symmetric and normal. To test for normality one has to calculate the returns on the associated indices mentioned above through the standard log returns formula:

Equation 2-Log Returns

$$R_t = \ln\left(\frac{S_{t+\Delta t}}{S_t}\right) = \ln S(t + \Delta t) - \ln S(t)$$

The calculation will be performed for the whole period and then implied distribution will be compared to the theoretical normal distribution. Given previous research emphasis on importance of skewness, statistics on skewness will be provided for each of the markets. The same procedure will be applied to the returns of the portfolio to confirm the results received in this section.

The last section of Part I will deal with the main hypothesis (I-H2) that has to do with testing of beta coefficient and the alternative risk measures. In this section, the testing will be performed for all of the countries in Table 1. To perform the analysis, firstly the author will estimate the coefficients numerically, and then run simple linear regression of the type suggested by Estrada (2000, p. 22).

Equation 3- Simple Linear Regression for RV

$$MR_i = \gamma_0 + \gamma_1 RV_i + u_i$$

Where MR_i is mean return and RV_i is the risk variable. Similarly, to previous research this paper will analyse several risk measures:

- Beta (measure of systematic risk)
- Standard deviation (measure of total risk)
- Semi-standard deviation (measure of total downside risk)
- Downside Beta (measure of downside risk)

The justification of the use of these measures can be summarized as:

- Beta was chosen as the most common measure of systematic risk.
- Total risk measure (standard deviation) was chosen due to its good performance in partially integrated markets (Estrada 2000, p. 21).
- The downside risk measures were chosen as an alternative to above-mentioned tools.

As has been mentioned previously, for this section of the research the coefficients will be calculated numerically for the period starting from 01/01/2000 and finishing with 31/12/2016. Thus, it is important to highlight what formulas were used.

5.3.1 Calculation of Beta Coefficient

The first section coefficients will be calculated numerically to avoid the necessity of estimation of risk-free rates for each country. Even though standard deviation and variance are standard measures that do not involve complex calculation, beta calculation is a bit trickier than the others are. The reason is the estimation of correlation between the emerging equity market and the world market. The general formula for beta coefficient has the following form:

Equation 4- Beta Coefficient

$$\beta_i = \frac{\sigma_{iM}}{\sigma_i * \sigma_M} * \frac{\sigma_i}{\sigma_M} = \rho_{iM} * \frac{\sigma_i}{\sigma_M}$$

Estrada (2005, p. 172)

The complication is rooted in finding appropriate representation of the world market. According to the past papers (Harvey 1996, Estrada 2004, Godfrey and Espinosa 1995), MSCI World Equity Index is a reliable estimation of the world equity market. Therefore, for this research paper, MSCI World Equity Index will be used for calculation of correlation coefficient on individual index (or market) with the world market. The period of the study will cover from 01/01/2005 up until 31/12/2016.

5.3.2 Calculation of Downside Beta

In the previous section, standard systemic risk measure – beta has been introduced. Since the aim of this paper is to compare the traditional risk measures such as standard deviation and beta to the alternative measures such semideviation and downside beta, it is important to define their calculation. The difference between the measures is rooted in the theories that underlie the models. As has been mentioned before the traditional beta is associated with MVB, which accounts for both upward and downward volatility, whereas downside beta is based on MSB, which focuses on negative volatility.

Equation 5-Downside Beta

$$\text{If } R_{it} - E(R_i) = [\min(R_{it} - E(R_i), 0) + \max((R_{it} - E(R_i), 0)]$$

We can then obtain:

$$\min(R_{it} - E(R_i), 0) + \max((R_{it} - E(R_i), 0) = b_{i2}\min(R_{mt} - E(R_m), 0) + \max((R_{it} - E(R_i), 0) + \varepsilon_{it}$$

Multiplying both sides by $min(R_{it} - E(R_i), 0)$ and taking expectation operator we get

$$E[min(R_{it} - E(R_i), 0)\ min(R_{it} - E(R_i), 0)] + \mathrm{E}[\max(R_{it} - E(R_i), 0) min(R_{it} - E(R_i), 0) = b_{i2}\mathrm{E}[\min(R_{mt} - E(R_m), 0)]^2 \text{ which reduces to}$$

$$\beta_i^D = \frac{E[\min(R_i - \mu_i)\min(R_m - \mu_m)]}{E[\min(R_m - \mu_m)]}$$

Estrada (2005, p. 172)

Where: R_i − return on the asset ; R_m − Return on the market portfolio;

μ_m − average return of the market and μ_i average return of the portfolio;

It is important to highlight that this is just one of the ways in which downside beta can be calculated, others include Bawa and Lindenberg (1997) and Harlow and Rao (1989).

5.4 Part II: Methods of Analysis and Testing

When testing asset pricing models, the dominating method in the majority of the papers is connected to cross-sectional regression (see Estrada (2000, 2004); Black, Jensen, Scholes (1972); Fama and French (1992) etc.). This tool is used to regress the mean excess return over a time interval for a set of securities (this can be either set of stocks or indices) on the estimates of systematic risk coefficients. The regression equation for such a test is a standard linear regression, which has been quoted in the Part I analysis. However, this is not the only way in which one can test asset-pricing models. Furthermore, according to Black, Jensen and Scholes (1972) due to the structure of the process these tests of significance can lead to quite misleading results, consequently not offering to the examiner direct proof of the model validity. Thus, in this research paper the author will apply both cross-sectional regression and time series test suggested Black, Jensen and Scholes (1972, p. 6).

5.4.1 Time series Tests

Even though the model that we will be testing (CAPM and D-CAPM) is stated in terms of expected returns, it is still possible to use realized returns to test the theory.

Equation 6- CAPM Regression Equation

$$E(R_j) = \beta_j E(R_M)$$

Where: $E(R_M)$ - expected excess return on the market portfolio and $E(R_j)$ - expected excess return on the portfolio. It is important to note that expected excess returns on a portfolio include dividends:

Equation 7 - Excess Return Calculation

$$E(R_j) = \frac{E(P_t) - P_{t-1} + E(D_t)}{P_t} - r_f$$

Let us firstly broadly redefine the model under the investigation, and express the returns on any security/portfolio in terms of "market model" that was originally proposed by Markowitz (1959) and later on extended by Sharpe (1963), and Fama (1968):

Equation 8- Market Model

$$R_j = E(R_j) + \beta_j R'_M + \varepsilon_j$$

Where the R'_M is the unexpected excess market returns. Both R'_M and ε_j are normally distributed random terms that must satisfy:

Equation 9 – Model Conditions

$$E(R_M) = 0$$

$$E(\varepsilon_j) = 0$$

$$E(R_M \varepsilon_j) = 0$$

The last term denotes the covariance between the unexpected excess return on the market and the expected random variable (error term). When we substitute from Equation 5 for CAPM into the market model, we get:

Equation 10 - Time Series Test Regression

$$R_j = R_M \beta_j + \varepsilon_j$$

Where R_j and R_M are the ex-post excess return on the risky assets and market portfolios over a given period of time. Given that the first relationship holds for each interval of time and the general asset pricing Equation (5) prices all of the securities, we can test the CAPM model by adding an intercept α_j to our last equation, which results into the following linear regression:

Equation 11 - CAPM Regression Model with Constant

$$R_j = \alpha_j + R_{Mt} \beta_j + \varepsilon_{jt}$$

If all of the above-mentioned asset pricing models are valid, then the intercept should be equal to zero. Thus, the first testing that can directly assess the validity of the model can be executed through running the regression above for each period to see if alpha is significantly different from zero.

The test that has just been discussed is simple in terms of logic and computation but not ideal since it concerns only one security, to avoid an aggregation problem it is suggested to run it on portfolios.

5.4.2 Cross-Sectional Tests

Time series testing is convenient in its simplicity; it is not applicable to multi-factor models such as Fama-French or even two-factor models such as the one suggested by Tobin (1958) and Markowitz (1959). Thus, to test these models one should employ different type of tools. One of the most common methods is cross-sectional testing. In this research, the author's main goal will be to perform similar analysis as has been done by Fama and French (1992) in their paper "*The Cross-Section of expected Stock Returns*".

Opposed to the previous section, all coefficients for testing of the portfolios will be estimated through running regressions:

Equation 12 - Regression Models CAPM and CAPM FF

$$\text{Traditional CAPM: } R_p - R_f = \beta_p\left(R_m - R_f\right) + \varepsilon_t$$

$$\text{Fama-French 3 Factor Model: } \quad R_p - R_f = \beta_p\left(R_m - R_f\right) + \beta_S SMB + \beta_V HML + \varepsilon_t$$

The calculation of coefficients in case of traditional CAPM and CAPM with 3 factors do not require any adjustments in the regression model. However, the calculation of downside beta requires several modifications as we are aiming to account only for downside comovement with the market. If we would run the following regression,

Equation 13 - DCAPM Regression

$$y_t = \beta_0 + \beta_1 * x_t + \varepsilon_t$$

$$x_t = \min[(R_{Mt} - \mu_M), 0] \text{ and } y_t = \min[\left(R_{pt} - \mu_p\right), 0]$$

we will get the following estimate of β_1

$$\beta_1 = \frac{E[(x_t - \mu_x)\left(y_t - \mu_y\right)]}{E[(x_t - \mu_x)^2]}$$

This is a standard estimate; however, for the proper estimation of downside beta we would need to have the following:

$$\beta_1 = \frac{E[x_t * y_t]}{E[x_t^2]}$$

To obtain such an estimation Estrada (2005, p.173) has suggested to run a simple regression that would regress y_t against x_t without a constant. The slope of this regression will yield downside beta.

$$y_t = \beta_1 * x_t + \varepsilon_t$$

Once all of the coefficients are defined, the aim of this analysis is to spot patterns in the spreads of beta and downside beta coefficients for each of the portfolios and see if they are significant and can explain the variations in the returns for each of the portfolios. Similarly, to the traditional CAPM adding extra factors to the D-CAPM model would allow seeing if downside beta would still be significant and have the same explanatory power. The equation for beta estimation with extra factors can be specified as:

Equation 14 - D-CAPM 3 factor Model

$$y_t = \beta_1 * x_t + \beta_S SMB + \beta_V HML + \varepsilon_t$$

The reason why the author decided to include testing of CAPM models with increased number of variables is to check if the is any specification bias. This bias emerges when the model is miss-specified; this particularly means that some of the variables are omitted. In our case, we would like to test if size and value should be added. In case these variables are significant, there is specification bias in the original model. In general, if this is the case the estimates of beta and downside beta respectively would not be an unbiased estimates of the true betas (Gujarati 1995, p. 205). This would result into receiving beta that is equal to the following expression:

Equation 15 - Biased estimates of Beta

$$b_2 = \beta_2 + \beta_3 b_{32} + \beta_4 b_{42} + error\ term$$

Where b_2 is the estimate of true beta coefficient and β_3 and β_4 are the missing coefficient where b_{32} and b_{42} are the slopes coefficient in the regression of excess markets returns on SML and HML respectively. After the beta coefficient is re-estimated the author will then check if the relationship between beta and returns still holds significant.

The above regression functions are commonly termed first-step regression. To perform cross-sectional testing one must perform two-step regressions, where the second step is the same as in case of cross-sectional testing on indices (see Part I).

5.5 Regression Methods

In the previous sections, we have looked at the regression functions and general concepts of the type of regression that will be performed during this study. This section will focus on technical specification of methods used to carry out regression. The most well-known options are either Ordinary Least Squared method (OLS) or the General Least Square. When it comes to OLS, it will yield unbiased and efficient estimates only in case certain conditions are met. These conditions are connected to the properties of the error process that we have listed in the Time Series Testing section. In general, OLS is optimal only when the error term is generated by an independent and identically distributed process (Alexander 2008, p. 148).

Even though, OLS method is often used in asset pricing, in past decade academics have systematically preferred GMM (Generalized Method of Moments.) GMM was introduced by Hansen (1982) and is particularly useful for scenarios when full shape of distribution is not defined or when the research does not want to impose assumptions on the distribution. The preference of GMM over OLS can be attributed to endogeneity problem that occurs due to correlation of explanatory variable with an error term. This can be a result of a number of issues such as (1) autoregression and autocorrelation of error terms or (2) quite common correlation between independent and depend variables and (3) and conditional heteroscedasticity. In CAPM model, the explanatory variable of excess market returns can be well correlated with the excess returns of the security or a portfolio. GMM is the only estimation method that allows dealing with this problem. Thus, for both Time Series test and the cross-sectional regression GMM will be used. According to Cochrane (2005, p. 233) GMM can be used for estimation of expected-return beta models and the usual OLS moments remain for estimation of parameters. Thus, above-mentioned tests apply, but in a slightly adjusted format:

Equation 16 - GMM Estimation

$$R^e = \alpha + \beta f_t + \varepsilon_t$$

This is the equation for all of the N assets in a vector form. Then we use standard moments to estimate beta coefficients:

Equation 17 - GMM Moments

$$g_t(b) = \begin{bmatrix} E_T(R^e - \alpha - \beta f_t) \\ E_T(R^e - \alpha - \beta f_t) f_t \end{bmatrix} = E_T\left(\begin{bmatrix} \varepsilon_t \\ f_t \varepsilon_t \end{bmatrix}\right) = 0$$

These moments define alpha and beta coefficients and yield the following estimates:

Equation 18 - GMM parameter estimates

$$\hat{\alpha} = E_T(R^e) - \hat{\beta} E_T(f_t),$$

$$\hat{\beta} = \frac{E_T[\left(R^e - E_T(R^e)\right) f_t]}{E_T[\left(f_t - E_T(f_t)\right) f_t]} = \frac{cov_T(R^e, f_t)}{var_T(f_t)}$$

According to Cochrane (2005, p. 208) by translating OLS regression into GMM we correct for standard errors that are autocorrelated and exhibit conditional heteroskedasticity. Similarly, to the study done by Tahir, Abbas, Sargana, Ayub and Saeed (2013, p. 125) for the first step regression, the author will use Newey-West estimator adjusted GMM, which will ensure parameter robustness corrected for heteroscedasticity and autocorrelation, whereas for cross-sectional regression White's estimator will be implemented to ensure for t-test statistics robustness.

5.5.1 The Sample Periods

When testing different risk measures, it is particularly important to include periods of high volatility that would represent uncertainty. During such periods, investors are becoming more sensitive to risk and there are more deviations from normality. Ideal study would include pre-periods that are associated with the Great Depression and recovery from Second World War; however, complete data for this period is available only for the US equity market. Thus, this study will focus on the period of recent financial crisis 2007-2008. It will particularly look at the distribution of returns during the period of 2004-2009, which can be associated with the start and later on the peak of the crisis.

In order to test for stationarity of beta and alpha coefficients, the sample period will be divided into equal sub-periods of 15 years each for the US and 5 years each for India, simple regression will be carried out using the data for each of these periods for the 6 portfolios.

5.6 Missing values

In the majority of the research connected to emerging markets and their equity markets, researchers face issues with missing values. This research is not an exception. When looking at the India portfolio data, it has been identified that several months have missing values in the Portfolio 1. Since the data included high frequency data of daily observations, this amounted to quite substantial number of missing observations. Generally, there are several approaches to treatment of missing values:

1. Ignoring the missing values or in other words exclude the observation from the sample.
2. Imputation methods that contain linear interpolation, cubic spline, log-linear interpolation etc.
3. Advanced imputation methods: simulation and maximum likelihood estimations

It is important to highlight that one should consider the reason why the values are missing. There are two possibilities either the values are missing at random or the reason why the values are missing is connected to the model and the parameters used inside of the model. The first case is the most favourable case, since if the values are missing at random the researcher can exclude the variables and be sure that there will not be a bias in the estimates. The author, assumes that the observations for the portfolio 1 are missing due to administrative reasons which are not connected to returns themselves, thus it can be concluded that the values are missing at random and to avoid problems with their simulation the author will exclude the period from 2004-2005 and from 2006-2007 from investigation.

5.7 Outliers

It is well-know from vast academic literature that both correlation coefficients and the regression functions are highly affected by the outliers present in the data. It is crucial to highlight that each of the observations provide information about the data distribution, therefore there is an inherent trade-off between keeping the information and finding a better fitting model. Consequently, one should pay attention to the chosen method. In this paper, the author is using a combination of four methods for identification of simple outliers and regression outliers: (1) Labelling Rule, (2) Z-score and (3) Cook's Distance and (4) studentized residuals. Along with the two-dimensional, scatter plots of all of the relationships. As the result for all of the variables and regressions, the author applied all of these methods to confirm that the same outliers are identified. Thus, the observation were removed only if they were identified as regression outliers that are influential.

Labelling rule is based on 25th and 75th percentile, if the observation lies above the upper quartile or below lower quartile, it is removed. This procedure is performed through boxplots created with the use of SPSS. Since this method is less sensitive to extreme values if nothing is identified but the results are still insignificant the author decided to check for outliers using the Z-score approach. This approach was used both for individual variables and for regression residuals.

Equation 19 - Z-score calculation

$$Z = \frac{x_i - \bar{x}}{\sigma} \text{ Where } x_i \sim N(\mu, \sigma^2)$$

The z-score is based on mean and standard deviation, where it is assumed that if the variable "X" follows normal distribution, "Z" should follow standard normal distribution, meaning that observations with Z-score over 3 are generally considered outliers. However, according to Schiffler (1988), in small sample sizes, which is the case of this research, the Z-score of three will never be reached. Thus, the limit should be set to lower level. In this research, the Z limit will be set to two. The author would like to specify that in case of z-score outliers are not removed at once, however one by one and separately for each variable. Furthermore, the samples are checked for outliers each time coefficients are re-estimated. This is particularly important for the case where extra explanatory variables are added. Lastly, Cook's distance was used to identify outliers that are influential observation and studentized residuals tests were used to confirm outliers identified by the previous two methods. This testing has been performed in R.

It is important to highlight that all of the identified outliers before being removed were checked on the two-dimensional scatter plot to confirm that they are situated far away from the fitted line.

5.8 Limitations

One of the main limitations of the above methodology lies in the construction of portfolios and availability of the data. Firstly, there were some missing values in the first portfolio for the Indian market. To account for this problem the author had to exclude this period from testing. Secondly, when performing testing it is important to use properly ranked portfolios and the ideal case would require ranking based on the risk variable, which is under the investigation. Thus, the portfolios that were used for this research are not fully serving the purpose. Unfortunately, portfolios that would be formed based only on size were not available for the Indian market and therefore there was no opportunity to rank portfolios based on size and riskiness opposed to size and value. This limitation of course plays quite a significant role in testing, however still allows checking the explanatory power of beta and other risk measures, which was the main purpose of this study. Another issue was related to the number of portfolios. For developed markets and Asia Pacific, French library offered 6 and 25 portfolios formed on size and value, whereas for India only six portfolios were available. As the result, this lead to limitations when it comes to running second-step regression. Moreover, to make consistent conclusion about the EMs, which possess high market promiscuity, it is necessary to construct portfolios for more than one country, compare, and construct the results.

Lastly, but not least important the author wants to highlight that this research focused on traditional methods of testing and thus did not include more sophisticated models that would potentially be of higher relevance.

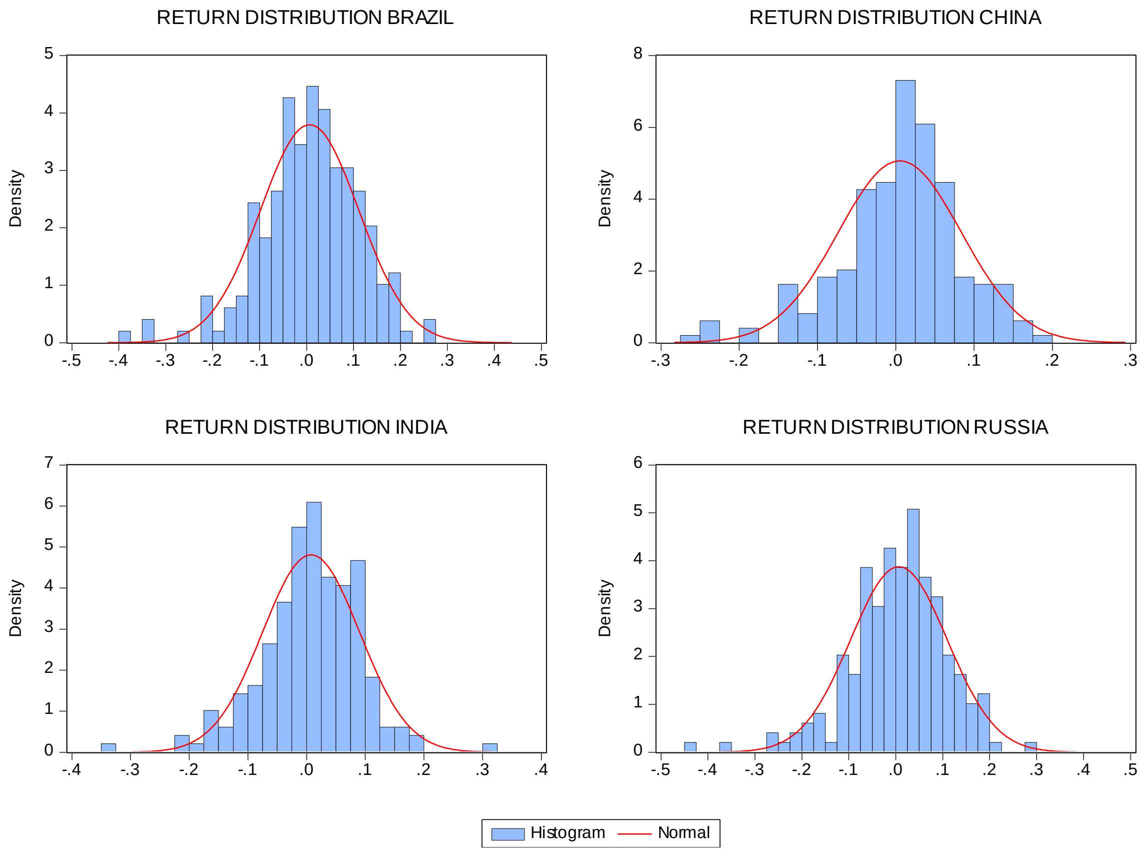
6 Empirical Results

6.1 Return Distribution Analysis

The first hypothesis of this research dealt with an assumption of normally distributed returns. This hypothesis is connected to the fundamentals of the CAPM model, represented by the Mean-Variance Behaviour, which assumes that the whole distribution can be described through the first two moments – mean and the variance. To test for this assumption one could do a graphic representation of the returns and search for excess kurtosis and skewness, which are the third and the fourth moments of the distribution. Past literature outlines that even developed markets show signs of fat tails. Per the main characteristics of normal distribution, it must be symmetric around the mean and it must have kurtosis equal to three.

The first step would be to consider return distribution for indices (see appendix), under the investigation. It is evident from the graphs that the return distribution for all the indices is non-normal, exhibits excess kurtosis and skewness. Below, one can see graphical representation of return distributions for BRIC countries. One common characteristic that all four indices share are fat tails from the left-hand side and leptokurtic shape of distribution.

Figure 1- Return Distribution BRIC



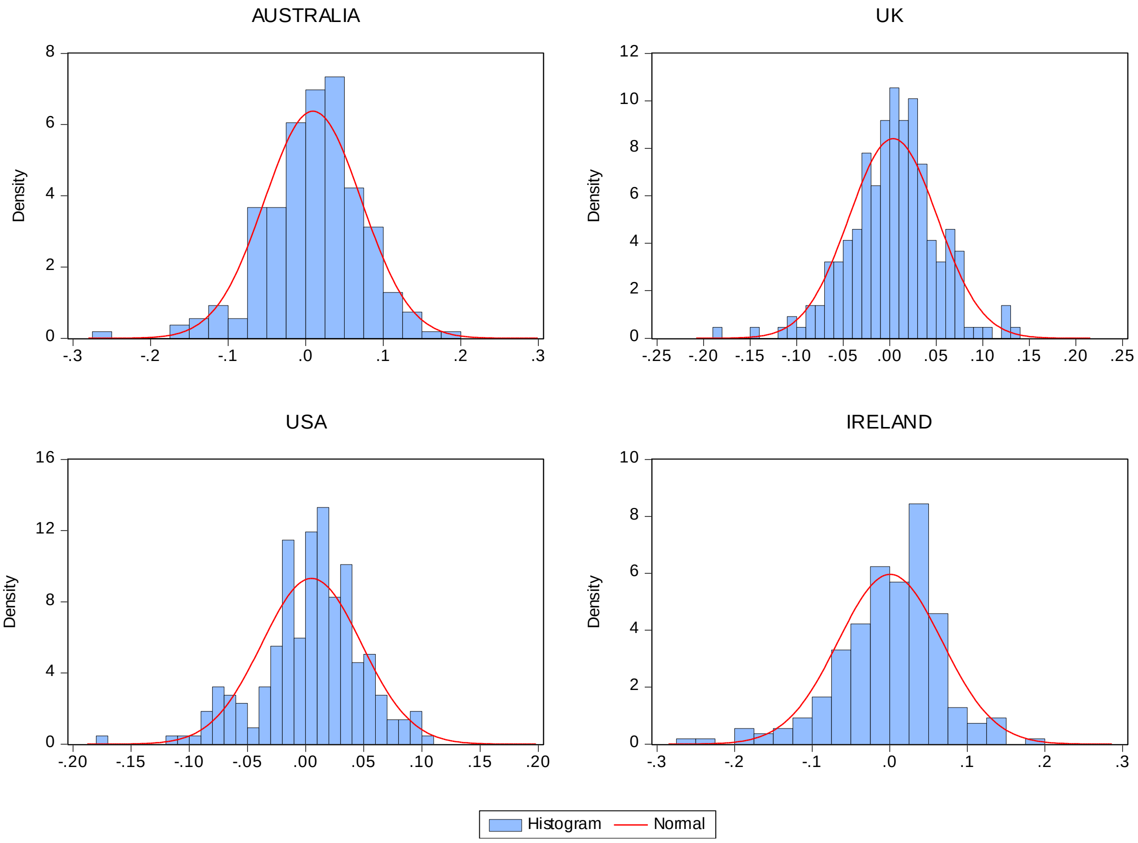
To support this graphical conclusion, let us consider distribution statistics. As one can see from the table below Jarque-Bera test is showing significant departure from normality since for all the indices we can see that the p-value is equal to zero. Furthermore, the kurtosis for three countries is higher than three, showing that there are fat tails.

Table 5 - Distribution Statistics BRIC

	CHINA RETURN	BRAZIL RETURN	INDIA RETURN	RUSSIA RETURN
Mean	0.52	0.67	0.77	0.70
Median	1.26	1.14	1.32	1.81
Maximum	18.18	26.64	31.24	27.70
Minimum	-25.80	-38.64	-33.51	-43.50
Std. Dev.	7.88	10.52	8.29	10.29
Skewness	-0.65	-0.53	-0.41	-0.76
Kurtosis	3.97	4.09	4.68	4.85
Jarque-Bera	21.75	19.06	28.53	47.02
Probability	0.000019	0.000073	0.000001	0

If we consider DM in representation of Australia, UK, USA and Ireland. We can see that these four countries also exhibit excess kurtosis (see Table 6), similar to EM.

Figure 2 - Return Distribution Developed Markets



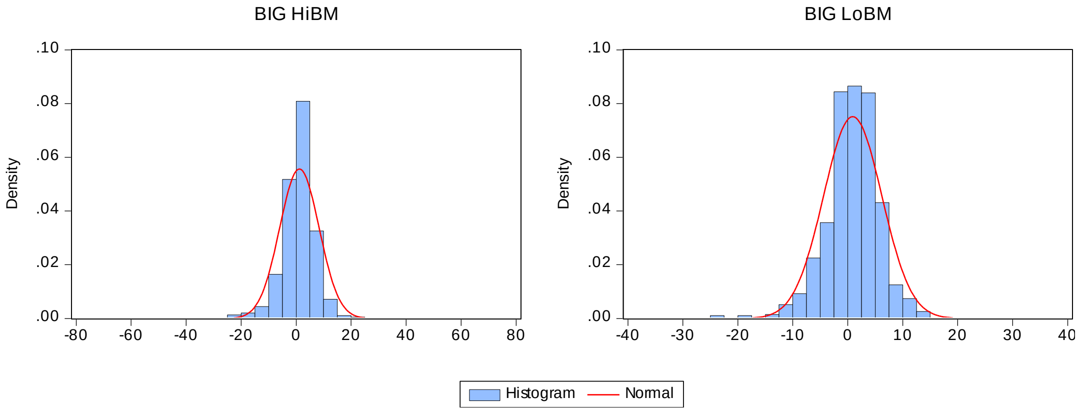
Furthermore, the distribution also shows quite strong negative skewness and fat tails. This trend repeats for all the counties under investigation. The Jarque-Bera coefficient was significant for all 26 countries in EM and 23 countries in DM, showing that there is a departure from normality (see the appendix). Secondly, all the countries have shown at least some excess kurtosis, meaning that all of them have fat tails. Moreover, for all the countries the fat tails are located at the left-hand side confirming that all the distributions exhibit negative skewness. As the result, the reasoning behind the downside risk measures can be regarded as quite strong. Consequently, H1 can be accepted for all the countries under investigation.

Table 6 -Return Distribution Statistics Developed Markets

	AUSTRALIA	UK	USA	IRELAND
Mean	0.009527	0.003755	0.005175	0.000550
Median	0.011468	0.005753	0.009487	0.009082
Maximum	0.177945	0.138710	0.109866	0.192186
Minimum	-0.255098	-0.189606	-0.171016	-0.260444
Std. Dev.	0.062576	0.047447	0.042842	0.066924
Skewness	-0.481838	-0.338286	-0.518665	-0.770011
Kurtosis	4.437647	4.308956	3.990115	4.673996
Jarque-Bera	27.20911	19.72098	18.67881	46.99651
Probability	0.000001	0.000052	0.000088	0.000000

6.1.1 US Portfolio Return Distribution

Figure 3 - US Portfolio Return Distribution



To further confirm the above findings, it is important to look at the distribution of returns for the six portfolios under the study. The distribution of all the portfolios exhibit asymmetricity and fat tails (see appendix). Based on the statistics that can be seen in the table below these conclusions are fully confirmed as kurtosis for all the portfolios exceeds 8 points. The deviation from normality for all of US portfolios is also confirmed by the Jarque-Bera statistics.

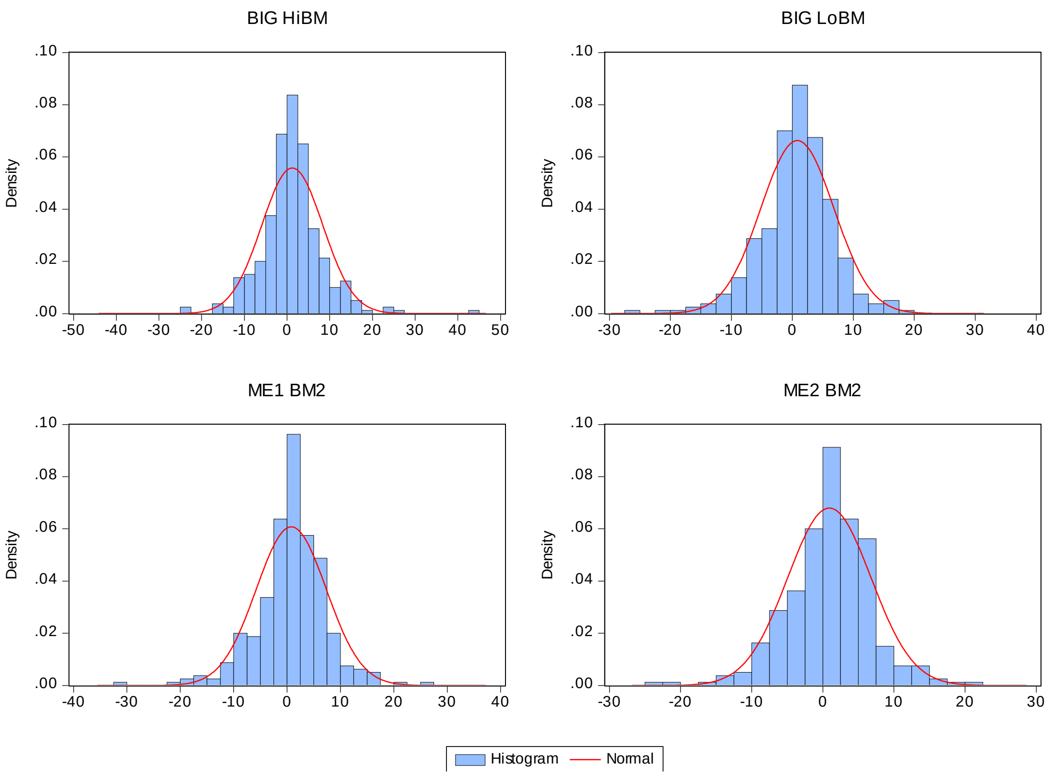
Table 7 – US Portfolio Distribution Statistics

Measures	_1_PORTFOLIO	_2_PORTFOLIO
Mean	1.197864	0.903867
Median	1.430000	1.220000

Maximum	67.78000	33.74000
Minimum	-35.11000	-28.87000
Std. Dev.	7.165103	5.307712
Skewness	1.570569	-0.115430
Kurtosis	21.02511	8.595825
Jarque-Bera	15148.40	1419.337
Probability	0.000000	0.000000

It makes sense to refer to other equity markets that fall under the umbrella of developed markets. In this paper, we will be testing asset pricing models on 6 Asia Pacific Portfolios. One can see the distribution of the log returns of first four portfolios below. It evident that all the portfolios exhibit excess kurtosis (leptokurtic) and left tails of the distributions are heavier than in case of normal distribution for all of the portfolios (fat tails).

Figure 4 - Asia Pacific Return Distribution



This can be confirmed by looking at the distribution statistics (see Table 8). One can see that as expected all four portfolios exhibit excess kurtosis and three out of four portfolios are negatively skewed. Furthermore, Jarque-Bera statistics is significant for all four portfolios, confirming departure from normality (see the rest of portfolios in Appendix).

Table 8 - Asia Pacific Distribution Statistics

	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	PORTFOLIO 4
Mean	1.23	0.83	0.79	0.92
Median	1.13	1.23	1.03	0.95
Maximum	42.64	18.83	26.44	21.31
Minimum	-24.99	-27.11	-32.47	-24.39

Std. Dev.	7.15	6.02	6.56	5.87
Skewness	0.55	-0.58	-0.54	-0.35
Kurtosis	7.56	5.25	6.01	5.06
Jarque-Bera	293.98	85.43	135.97	63.21
Probability	0.00	0.00	0.00	0.00

If we compare these results with Indian portfolios, we can see the same patterns. Though it is important to highlight that kurtosis in the return of the Indian portfolios is much more restrained. The distributions still is non-normal based on the Jarque-Bera test.

Figure 5 - Portfolio Distribution India

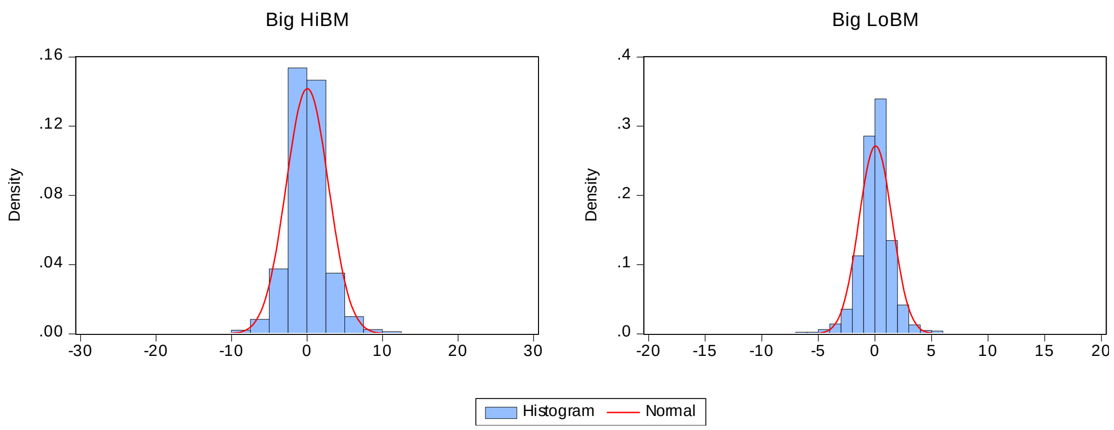


Table 9 - Portfolio Distribution Statistics India

Measures	PORTFOLIO 1	PORTFOLIO 2
Mean	0.049539	0.055489
Median	-0.034158	0.093395
Maximum	24.75730	15.82908
Minimum	-22.13740	-11.51981
Std. Dev.	2.812015	1.467281
Skewness	0.561437	-0.201037
Kurtosis	11.24735	9.593014
Jarque-Bera	14941.32	10347.46
Probability	0.000000	0.000000

Based on the above-results one can see that both developed and emerging markets share similar characteristics in return distributions and thus one would expect that downside risk measures should perform better than traditional risk measures for all countries. One can also cannot reject H1 for both indices and the portfolios in all the markets under investigation.

6.2 Part I: Risk Measure Performance Test on Indices

This part of the research paper focused on testing of four risk measures based on index returns from 26 countries of Emerging Markets and 23 Countries of Developed markets. The aim of this section is to test for the first set of Hypotheses (H.1.1 and H.1.2) specified particularly for Part I.

6.2.1 Emerging Markets

To start discussing the results lets firstly look at the mean returns represented in the Table 10. Firstly, it is important to observe that average monthly returns for the period under study are around 1%, for all the countries, which is quite low given higher risk inherent to these markets. The drastic negative movements in the stock prices during the times of the crisis of 2007-2008 and much slower recovery can explain this trend.

All of the risk measures are calculated with the respect to the MSCI World Total Return Index. This part will be comparing the explanatory power and association of the risk measures that are related to the following four models:

Equation 20 - Tested Models Part I

$$E(R_p) = R_f + \frac{\sigma_i}{\sigma_M}(R_M - R_f)$$

$$E(R_p) = R_f + \frac{\sum_i}{\sum_M}(R_M - R_f)$$

$$E(R_p) = R_f + \beta(R_M - R_f)$$

$$E(R_p) = R_f + \beta^D(R_M - R_f)$$

Two of the models look at total risk opposed to the systematic risk. These models determine the risk premium based on the ratio of standard deviation of portfolio to the standard deviation of market or semideviation when it comes to downside risk measures. As the result, one can describe these models also as models that assume that the correlation between the portfolio and the market is equal to one. This means that because of this assumption we are also pricing diversifiable risk. Before looking at the relationship it is always necessary to look at the statistics and examine if there any outliers. In this case, one outlier (Colombia) was identified for all of the risk measures based on z-score. There were other outliers for each separate second-step regression based on Cook's Distance (see appendix), however since all of the regression were statistically significant the author has decided to keep the observation as they also provide an information about how measures explain extreme cases.

Table 10- Risk Measures Index Results

Country	μ	σ_i/σ_m	β	$\sum_i/\sum_m$	β^D
Indian Return	1.06%	1.860	1.234	1.686	0.963
China Returns	0.82%	1.734	1.198	1.658	0.923

Colombia Returns	1.94%	1.947	0.945	1.804	1.048
Russian Return	1.28%	2.258	1.499	2.109	1.196
Czech Returns	1.28%	1.773	1.116	1.574	0.895
South Korea Returns	0.96%	1.890	1.382	1.619	0.918
Brazil Returns	1.28%	2.330	0.027	2.087	1.198
Indonesia Returns	1.64%	2.106	1.076	1.922	1.055
Mexico Returns	0.89%	1.488	1.178	1.441	0.807
South Africa Returns	1.07%	1.680	1.191	1.594	0.919
Pakistan Return	1.60%	2.074	0.474	1.876	0.968
Morocco	0.71%	1.235	0.410	1.020	0.588
Egypt	1.32%	2.221	0.996	1.912	1.084
Chile	0.81%	1.408	0.901	1.268	0.686
Argentina	1.78%	2.709	1.167	2.239	1.251
Turkey	0.95%	2.945	1.826	2.677	1.546
Thailand	1.35%	1.856	1.086	1.677	0.931
Poland	0.72%	2.113	1.533	1.812	1.042
Peru	1.66%	1.894	0.989	1.706	0.949
Jordan	0.53%	1.272	0.294	1.075	0.590
Israel	0.39%	1.437	0.920	1.364	0.721
Hungary	1.04%	2.231	1.605	2.078	1.136
Taiwan	0.48%	1.638	1.079	1.429	0.827
Sri Lanka	1.35%	2.272	0.561	1.554	0.867
Philippines	1.00%	1.580	0.775	1.425	0.810
Malaysia	0.62%	1.180	0.664	1.112	0.634

Looking at the correlation between mean returns and the four risk measures that have been chosen for testing we can see quite different results to what has been found before:

Table 11 - Correlation between Risk Measures and Returns

Correlations

		Mean	Std	Beta	Semideviation	Downside Beta
Mean	Pearson Correlation	1	.611**	.017	.602**	.523**
	Sig. (2-tailed)		.001	.936	.001	.007
	N	25	25	25	25	25
Std	Pearson Correlation	.611**	1	.408*	.937**	.949**
	Sig. (2-tailed)	.001		.043	.000	.000

	N	25	25	25	25	25
Beta	Pearson Correlation	.017	.408*	1	.475*	.529**
	Sig. (2-tailed)	.936	.043		.016	.007
	N	25	25	25	25	25
Semideviation	Pearson Correlation	.602**	.937**	.475*	1	.961**
	Sig. (2-tailed)	.001	.000	.016		.000
	N	25	25	25	25	25
Downside Beta	Pearson Correlation	.523**	.949**	.529**	.961**	1
	Sig. (2-tailed)	.007	.000	.007	.000	
	N	25	25	25	25	25

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The strongest association can be seen between mean returns and standard deviation, followed by semideviation and then downside beta. However, it is important to notice that the difference between the correlation of standard deviation and semideviation is negligible. All the correlations are significant at the 0.01 level, which indicates higher precision of the association. Another crucial relationship is the correlation between standard deviation and semideviation (0.937), this relationship suggests that the association of total risk measure (standard deviation) with the mean returns goes largely through the downside risk. One can see that downside beta is the third strongest measure of association. Estrada (2000, p. 22) received similar results. However, this is quite a different outcome to his more recent papers (see Figure 6). Most of the papers also suggest using systematic downside risk measures and outline their priority over total risk measures.

Figure 6- Correlation Matrix Estrada 2005

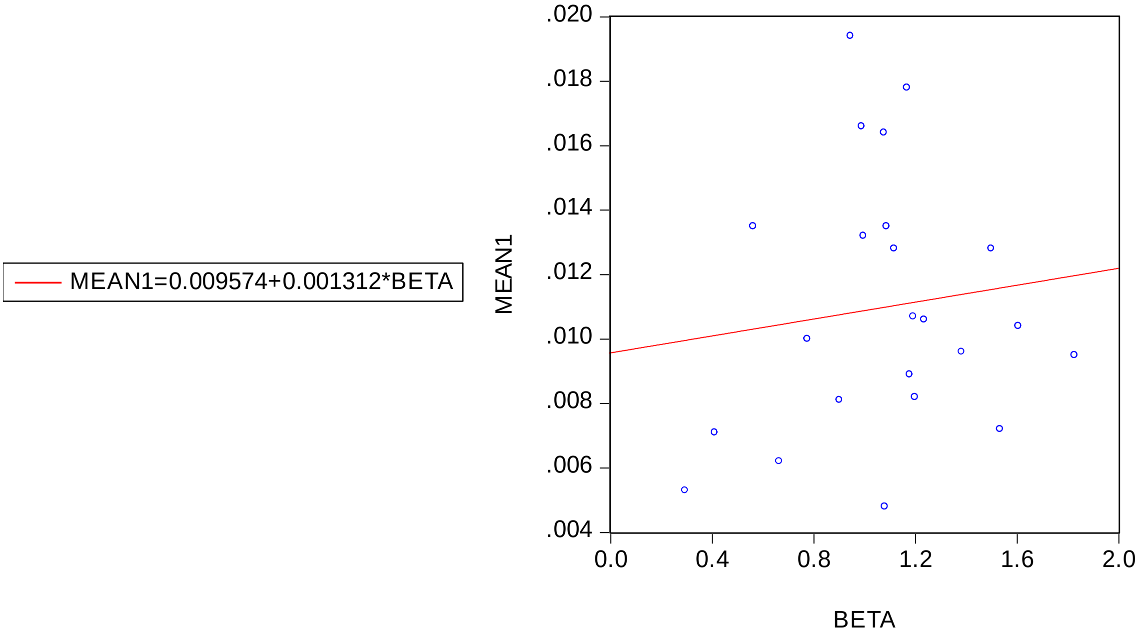
Full sample: correlation matrix

	MR	σ	β	Σ	β^D
MR	1.00				
σ	0.58	1.00			
β	0.54	0.53	1.00		
Σ	0.59	0.98	0.59	1.00	
β^D	0.69	0.88	0.83	0.90	1.00

MR: mean return; σ: standard deviation; β: beta (with respect to the world market); Σ: semideviation; β^D: downside beta (with respect to the world market).

Moreover, if one considers the relationship between mean returns and traditional beta we can see that there is no correlation. This can be confirmed if we regress, mean returns against traditional beta see Figure 8. As one can see, the regression line is quite flat and thus we can conclude that beta does not have explanatory power, as it cannot differentiate between high returns and low returns. This result contradict the main assumption of the traditional CAPM model that returns have a positive relation with beta coefficient.

Figure 7 - Mean Returns against Beta without outliers



Results that are more thorough can be obtained by running cross-sectional simple linear regression model, relating each of four risk measures to the mean returns. In order to account for heteroscedasticity all the regressions are based on White's heteroscedasticity-consistent covariance matrix and use GMM method of estimation. The results of cross-sectional regression, confirm previous hypothesis where the highest coefficient of determination (R-squared) is assigned to standard deviation. As per the results, approximately 37.31% of the variations in the mean returns can be explained by standard deviation and t-statistic confirms that lamba in front of standard deviation is significant. The second highest coefficient of determination belongs to semideviation that explains 36.20% of variations, followed by downside beta explains 27.39%. All of the models are statistically significant. It is crucial to highlight that beta is statistically insignificant according to the t-statistics and has R-squared of zero, which confirms previous findings of Harvey (1995). Furthermore, one can see that the intercept is statistically different from zero (Table 12), which contradicts the key assumption of CAPM model suggested by Sharpe and Lintner (1964) meaning, that zero beta securities receive some extra return, even though they do not bear any extra risk. If we compare these results to the ones in Figure 6, one can see that the main difference lies in the strength of standard deviation, which opposed to the previous results now is 1% higher than semideivation and downside beta is not as strong.

Based on the findings above, one can argue that investors should prefer to use the following models, instead of the classical CAPM and D-CAPM:

$$E(R_p) = R_f + \frac{\sigma_p}{\sigma_M}(R_M - R_f)$$

Or

$$E(R_p) = R_f + \frac{\Sigma_p}{\Sigma_M}(R_M - R_f)$$

Table 12 - Cross-Sectional Analysis Simple Regression

Eq Name: *Dep. Var:*	MEAN	MEAN	MEAN	MEAN
C	0.000688 [0.2405]	0.010482 [5.9312]**	0.000526 [0.2093]	0.002123 [0.6747]
STD	0.118023 [3.4049]**			
BETA		0.000153 [0.1143]		
SEMIDEVIATION			0.182369 [3.8289]**	
DOWNSIDE_BETA				0.008401 [2.6551]*
R-squared:	0.3731	0.0003	0.3620	0.2739

So far, we have looked at simple regression of mean returns against each of the risk measures. Another possible approach to testing would be to construct a multiple regression model of the type below:

$$MR_i = \gamma_0 + \gamma_1 RV_1 + \gamma_2 RV_2 + \varepsilon_i$$

This type of regression will be able to spot the significance of variables when they are considered together. The logic is similar to the one used in three-factor model suggested by Fama and French, where by adding extra factors they have identified insignificance of beta coefficient. In this paper, the author will consider three types of multiple regressions:

- Semideviation and standard deviation
- Standard deviation and downside beta
- Standard deviation, semideviation and downside beta

Beta has been excluded, as this risk measure was insignificant on its own. The results of the first regression can be seen in Table 13. The results are contradicting as semideviation is not significant and standard deviation can be considered significant at 6% or with greater certainty at 10% level.

Table 13 Multiple Regression Semideviation and Standard Deviation

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000858	0.003618	0.237182	0.8146
SEMIDEVIATION	-0.000319	0.004148	-0.076814	0.9394
STANDARD_DEVIATION	0.005637	0.002821	1.998252	0.0576

R-squared	0.321070	Mean dependent var	0.010974
Adjusted R-squared	0.262032	S.D. dependent var	0.004145
S.E. of regression	0.003561	Akaike info criterion	-8.329360
Sum squared resid	0.000292	Schwarz criterion	-8.184195
Log likelihood	111.2817	Hannan-Quinn criter.	-8.287558
F-statistic	5.438405	Durbin-Watson stat	2.547845
Prob(F-statistic)	0.011641	Wald F-statistic	6.248673
Prob(Wald F-statistic)	0.006802		

When a different set of risk variables is used (standard deviation and downside beta), one can see that only standard deviation is significant at 5% level, which again confirms previous finding.

Table 14 - Multiple Regression Standard Deviation and Downside Beta

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001023	0.003465	0.295125	0.7705
STANDARD_DEVIATION	0.007370	0.003400	2.167702	0.0408
DOWNSIDE_BETA	-0.004209	0.008753	-0.480912	0.6351

R-squared	0.326072	Mean dependent var	0.010974
Adjusted R-squared	0.267469	S.D. dependent var	0.004145
S.E. of regression	0.003548	Akaike info criterion	-8.336755
Sum squared resid	0.000290	Schwarz criterion	-8.191590
Log likelihood	111.3778	Hannan-Quinn criter.	-8.294953
F-statistic	5.564130	Durbin-Watson stat	2.468317
Prob(F-statistic)	0.010692	Wald F-statistic	8.464927
Prob(Wald F-statistic)	0.001758		

The last combination would be the one incorporating all of the risk variables. The aim of this combination is to identify if there is one dominant risk measures or if there are several. The results of this regression can be seen in Table 15. It is evident from the table that only standard deviation is significant at 10% level, and none of the measures are significant at 5%.

Table 15 - Multiple Regression 3 Risk Variables

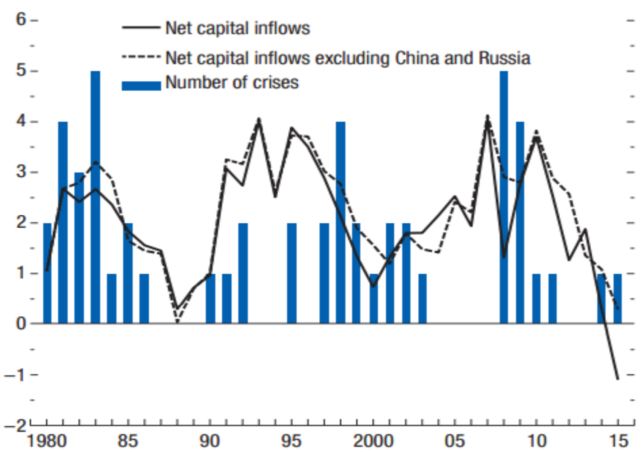
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000446	0.003245	0.137350	0.8920
DOWNSIDE_BETA	-0.024919	0.030697	-0.811773	0.4256
STANDARD_DEVIATION	0.005884	0.003009	1.955600	0.0633
SEMIDEVIATION	0.013643	0.016594	0.822116	0.4198

R-squared	0.347693	Mean dependent var	0.010974
Adjusted R-squared	0.258742	S.D. dependent var	0.004145
S.E. of regression	0.003569	Akaike info criterion	-8.292440
Sum squared resid	0.000280	Schwarz criterion	-8.098887
Log likelihood	111.8017	Hannan-Quinn criter.	-8.236704
F-statistic	3.908811	Durbin-Watson stat	2.368208
Prob(F-statistic)	0.022277	Wald F-statistic	6.079252
Prob(Wald F-statistic)	0.003563		

The superiority of total risk measures over systematic risk measures can be justified by an assumption that emerging markets are fully segmented, which contradicts a common view that EM are partially integrated. According to CAPM model in fully integrated markets, the cost of equity can be explained by beta, whereas for fully segmented markets total risk measures should be the most efficient. The reason why standard and semideviation are more efficient in case of segmented markets is that they imply that some of firm specific risk is non-diversifiable and thus investors are supposed to be compensated for it with the risk premium. This extra risk is not accounted for by systematic measures.

Figure 8 - Net Capital Inflows into Emerging Markets



Source: IMF 2016 Understand the Slowdown of Capital Flows into Emerging Markets, Chapter 2

One of the possible explanation of a change in the status of the integration of the financial markets could be attributed to the crisis that were experienced by financial markets for the period under investigation, which could cause segmentation of the markets. Particularly, this could be reasoned with less investment coming from advanced economies into EM. According to IMF (2016), the peak of net capital flows into EM was reached in 2010 and since then there has been a steady slowdown connected to tightening of the monetary policy in the US and other measures in the EU as well as general increase in global risk aversion reported by IMF (2017) Working Paper. All of this could have reversed the integration process.

The justification of superiority of standard deviation over semideviation can be attributed to the definition of semideviation as the difference in the explanatory power is quite low (just 1%). In this paper, the author defined semideviation as any movement below the mean returns, but in this case, it might make more sense to look at the movements below the risk-free rate. These calculations are however beyond the capacities of this research. Furthermore, Galagedera (2006, p. 16) attributed power of downside risk measures to skewness of returns, however in this case we could see that on average DMs exhibited higher kurtosis and skewness.

The above results confirm only one of the hypotheses set forward by this paper, the beta coefficient did prove to be significant, and showed no correlation with the mean returns. However, when we look at hypothesis I-H1, it cannot be accepted as the highest explanatory power throughout all of the tests has been shown by the standard deviation not the downside risk measures. Nevertheless, it is worth to mention that the difference is minor. As the result, the author's hypothesis that downside beta is superior to traditional beta can be accepted, however with amendment that based on this sample of countries and the sample period, standard deviation would be preferred over all other risk measures considered.

6.2.2 Developed Economies Analysis

In the previous section, we have considered several countries falling under the emerging market umbrella, however to make a conclusion one would need to compare the results with the developed economies. One of the main assumptions that many of the authors put forward is that due to full integration of developed economies into the global financial markets the CAPM model and traditional risk measures should show higher explanatory power for the mean returns than in case of EM. One can find mean returns, and the four calculated risk measures in Table 16.

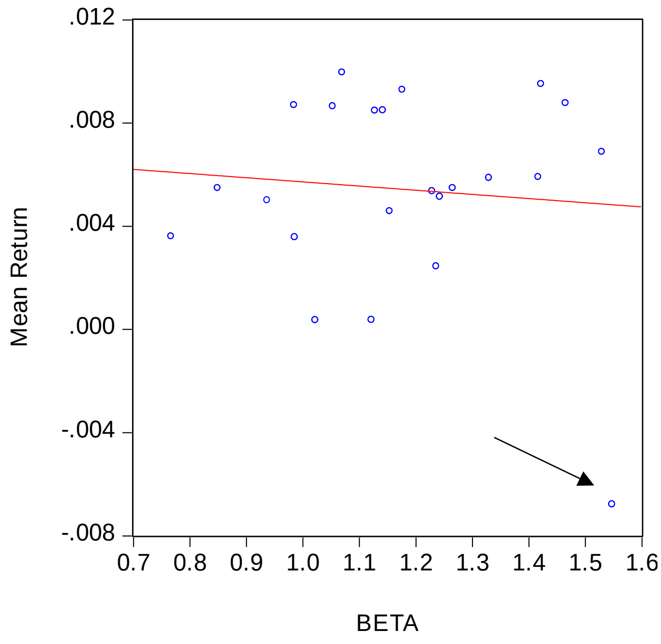
Table 16 - Developed Economies 4 Risk Measures

Country	μ	σ_i/σ_m	β	$\sum_i/\sum_m$	β^D
Austria	0.59%	0.08	1.330	0.062	1.070
Australia	0.93%	0.06	1.177	0.046	0.851
Belgium	0.46%	0.06	1.154	0.055	0.937
Denmark	0.99%	0.06	1.070	0.045	0.855

Finland	0.69%	0.09	1.530	0.063	0.960
France	0.51%	0.06	1.243	0.043	0.900
Germany	0.59%	0.07	1.417	0.050	1.029
Greece	-0.68%	0.11	1.548	0.081	1.147
Hong Kong	0.86%	0.06	1.053	0.043	0.771
Ireland	0.04%	0.07	1.122	0.052	0.874
Italy	0.24%	0.07	1.237	0.047	0.848
Japan	0.36%	0.05	0.767	0.031	0.560
Netherlands	0.54%	0.06	1.229	0.047	0.942
New Zealand	0.87%	0.06	0.985	0.045	0.706
Norway	0.95%	0.08	1.422	0.057	1.037
Canada	0.85%	0.06	1.128	0.043	0.825
Portugal	0.04%	0.07	1.022	0.045	0.694
Singapore	0.85%	0.07	1.142	0.051	0.880
Spain	0.55%	0.07	1.265	0.048	0.871
Sweden	0.88%	0.08	1.465	0.053	1.077
Switzerland	0.55%	0.05	0.850	0.033	0.651
UK	0.36%	0.05	0.986	0.033	0.707
USA	0.50%	0.04	0.937	0.032	0.703

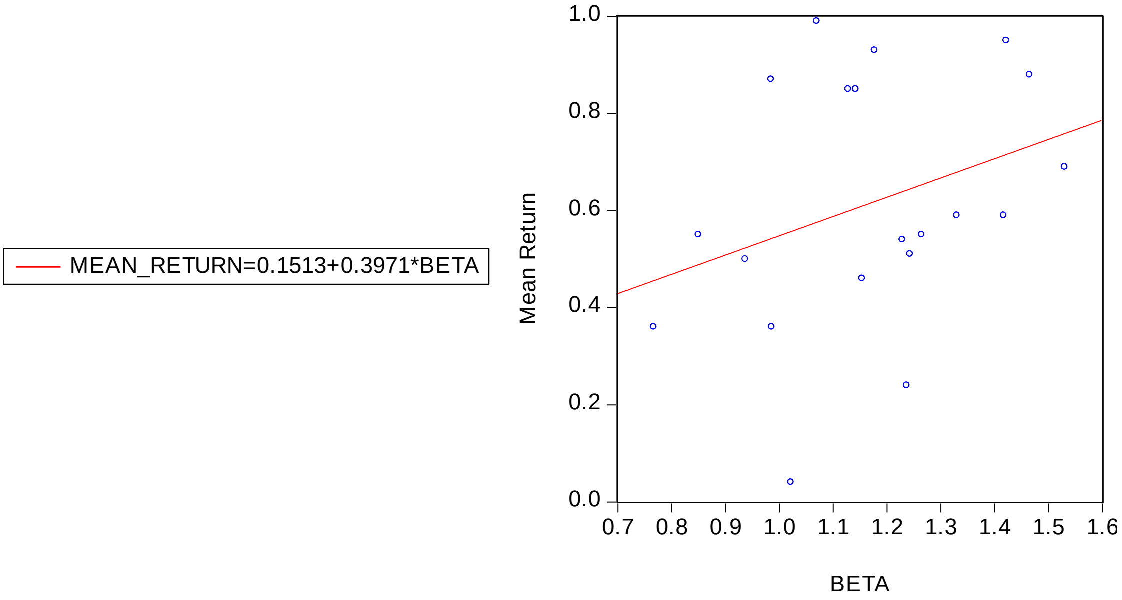
It is evident that on average DM earned less than emerging markets. When plotting the relationship between beta and mean returns it was evident that there are some outliers and thus to ensure that the regression model works well those had been removed. For identification of outliers, Cook's distance (see appendix) which has identified that for the majority of the risk measures Greece and Japan were the outliers, thus these observations has been removed.

Figure 9 - Beta against Mean Returns Plot Developed Markets



Once these observation were removed the relationship between beta and returns became positive as argued by the model (see Figure 10). One can still observe that the data is not homogenous and some points lie far from the regression line, suggesting quite high residuals.

Figure 10 - Beta against Mean Returns Plot



If we perform similar cross-sectional regression of all the risk measures against the mean returns, we will see that out of all the measures, the highest R-squared is assigned to downside beta, and this measure is statistically significant, explaining approximately 16% of the variation in the mean returns. The second highest is semideviation followed by beta (both measures are statistically significant at 5% level). This confirms the main hypothesis of this paper that downside risk measures are superior to traditional risk measures. It is interesting to notice that in this case standard deviation is statistically insignificant at 5% and only significant at 10%.

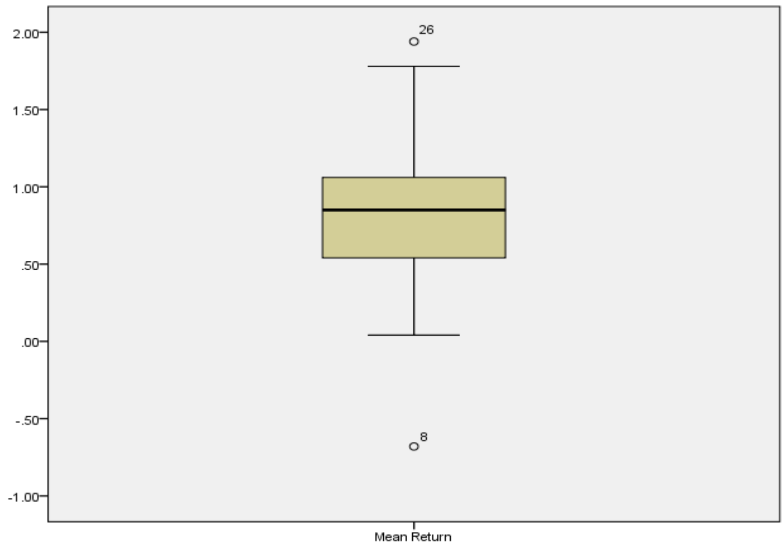
Table 17 - Second Step Regression Developed Markets

Eq Name:				
Dep. Var:		MEAN_RETURN		
C	0.151323 [0.7345]	0.308653 [1.8839]	0.194240 [1.0755]	0.006971 [0.0272]
BETA	0.397052 [2.3527]*			
STANDARD_DEVIATION		4.749568 [1.9053]		

SEMIDEVIATION			9.058340 [2.4603]*	
DOWNSIDE_BETA				0.711021 [2.4738]*
R-squared:	0.1008	0.0515	0.1047	0.1634

These results can be justified by the fact that developed markets are fully integrated and thus, diversifiable risk should not be priced. However, this also confirms hypothesis that investor care more about downside volatility than the positive volatility. To conclude this section, it has been decided to combine the two samples and see which of the measures would work the best for both developed and emerging markets all together. Before running aggregate regression, the author has identified two outliers (confirmed by all methods) in the whole set - observation 8 (Greece) and observation 26 (Colombia). These two observations have been removed from the sample.

Figure 11 - Outlier Identification Combined Sample



The results show some interesting trends, one can see that beta is insignificant and has intercept statistically significant from zero, which violates the main conditions of the traditional CAPM model. One can also see that the rest of the measures are significant and the strongest out of all the measures is standard deviation, which explain up to 45% of the movements. However, it is crucial to highlight that semideviation is explaining just 1% less. Downside beta is also significant explaining up to 25% of the movements in the mean returns. One can see that emerging markets had great influence in this sample, as in case of advanced economies alone standard deviation was not significant.

This results, confirm that downside beta should be preferred over traditional beta generally, however in case of emerging markets given this specific time frame the ratio of standard deviations is explaining more of variation (see Table 18).

Table 18 - EM and DM Second Step Regression Results

Eq Name: *Dep. Var:*		MEAN_RETURN		
C	0.934333 [5.2929]**	0.552463 [9.4923]**	0.560432 [9.8036]**	-0.114984 [-0.5826]
BETA	-0.081315 [-0.6082]			
STANDARD_DEVIATION		0.284426 [7.4007]**		
SEMIDEVIATION			0.313236 [7.1765]**	
DOWNSIDE_BETA				1.069636 [5.0025]**
R-squared:	0.0047	0.4569	0.4404	0.2511

6.3 Part II: Portfolio Testing

Before performing testing on the portfolios one of the preconditions is to check if the weak set of assumptions holds when running simple Classical Linear Regression Model (from here on CLRM). This is necessary to be able to understand what methods for regression estimation are more reliable. CAPM model is a type of a regression model that is parametric and non-random. For such a model, independent variables are assumed to be constant as well as the intercept. Thus, to understand the relationship between independent and the dependent variable, the properties of the residuals are important. There are five basic assumptions (strong set of assumptions) behind the CLRM:

- $E(u_t)= 0$
- $var(u_t) = \sigma^2 < \infty$
- $cov(u_t, u_j) = 0$
- $cov(u_t, x_t) = 0$
- $u_t \sim N(0, \sigma^2)$

Where $u_{t,j}$ are the residuals. What these assumptions essentially imply is that when one aims to calculate beta coefficient with the use of regression, the first step is to check if all of these conditions hold. The first assumption deals with the mean of the residual. The mean of the residual is assumed to be zero, which is always the case for regressions that include intercept. Thus, in this section this assumption will not be tested. Next, assumption implies testing for homoscedasticity. Homoscedasticity assumes that the variance of error terms is constant. To test for existence of heteroscedasticity, this paper will use White's test. In case there is heteroscedasticity, the estimates of the coefficients will still be unbiased however; the coefficient standard error will no longer be representative. The next assumption looks at the covariance between the error terms over time. The models stipulate that the correlation between the error terms should be zero, if this is not the case the error terms are said to be "autocorrelated". In case of autocorrelation, the coefficients again will be reliable however; the coefficient of standard error will be biased. In this section, we will use Durbin-Watson test for autocorrelation, which is the first order autocorrelation test. This implies testing only for the error and its immediate previous value (Brooks 2009, p.145). The last but not the least important is the test for the normality of the residuals. According to the model, the distribution of the residuals is supposed to be normal, thus, it should have no skewness and kurtosis equalling to three. In this paper, Bera-Jarque normality test will be used.

6.3.1 Summary for Testing the Strong Set of Assumptions

When running classical linear regression (method OLS) for all the stock portfolios of the US, and checking for the White statistics the null hypothesis can be rejected at the 5% significance level, meaning there is heteroscedasticity present. All the portfolios had p-values equalling to zero for both F-static and chi-square statistic (one can see results in the appendix). The same trend can be seen in the results for India and Asia Pacific. These results confirm previous research and consequently in all the further regressions, there will be a need to apply White or Newey-West adjustments.

When looking at the autocorrelation, as per the Durbin-Watson test none of the portfolios possess autocorrelation as the values of the DW coefficient is very close to two, which is the rejection region. Finally, the test for normality of the residuals has shown that for all the portfolios the null hypothesis can be rejected (see the p-values in the appendix). Meaning the distribution exhibit kurtosis, which confirms the previous findings in regards to distribution of returns, as in non-random regression characteristics of the residuals define the characteristics of response variable. As the result of this conclusion, Ordinary Least Squared method can be used with the adjustments, but one should prefer GMM (with adjustment White and Newey-West) as this method does not impose any distributional assumptions (Jagannathan, Skoulakis and Wang, 2002).

6.3.2 Time Series Test

In this part of the research related to the Hypothesis 2, the main idea is to test so-called non-zero intercept. In case of Sharpe-Lintner CAPM (1964), the intercept is assumed to be zero. This is commonly referred to as Jensen's alpha testing. If alpha is statistically different from zero it means that portfolio has been generating extra returns on the top of what has been expected. Based on previous research the author assumed that the alpha coefficients would be significantly different from zero in the later periods of the sample. The high-risk portfolios (beta greater than 1) will have a negative alpha, whereas low-risk portfolios (beta lower than 1) will exhibit positive alpha. Furthermore, at the early periods, the coefficients for high-risk portfolios might be positive but in the most recent periods, they would change the sign. Further extending this point, one could also look at the stationarity of the relationship be subdividing the period under investigation into sub-periods.

As has been mentioned previously the research includes six portfolios:

Table 19-6 Portfolio Description

Portfolio Number	Type of Portfolio	Riskiness
Portfolio 1	Big_HiBM	Average low size effect premium and high value effect premium
Portfolio 2	Big_LoBM	The least risky portfolio both of the premiums are expected to be low
Portfolio 3	Me1_BM2	Neutral portfolio (small neutral)
Portfolio 4	Me2_BM2	Neutral portfolio (big neutral)
Portfolio 5	Small_HiBM	The riskiest portfolio both premiums are high
Portfolio 6	Small_LoBM	Average risk high premium for size effect low for the value effect

Firstly, let us consider the results for aggregate period starting in 01/07/1926 and ending in 30/12/2016. In the Table 20 below, one can find results for all six US portfolios. What we can see is that only two out of 6 portfolios show significant difference of the intercept from zero, thus based on the aggregate testing the results are inconclusive and it would not be possible to reject the null hypothesis. What is also evident is that portfolio 5 (the riskiest portfolio) exhibits this differences, coefficient is positive meaning that portfolio earned something at the top of what CAPM predicted. We can also see that portfolios that have departures from zero intercept have the highest beta coefficients, as has been expected.

Table 20- Time Series Aggregate Results US

Eq Name: *Dep. Var:*	_1_PORTFOL IO-RF	_2_PORTFOL IO-RF	_3_PORTFOL IO-RF	_4_PORTFOL IO-RF	_5_PORTFOL IO-RF	_6_PORTFOL IO-RF
C	0.127693	-0.005898	0.212867	0.030054	0.333683	-0.131291
t-statistic	[1.3985]	[-0.1736]	[2.3826]*	[0.5738]	[2.6914]**	[-1.2558]
MKT_RF	1.214517	0.968645	1.186968	1.011039	1.324404	1.255726
	[71.9132]**	[154.1610]**	[71.8293]**	[104.3554]**	[57.7536]**	[64.9371]**

If we compare these results to the ones from the regressions done with the Indian portfolios constructed with the same logic, we can see similar trend the intercept is significantly different for portfolio 5 and 1, which confirms the general hypothesis that high-risk portfolios on average earned higher returns. However, opposed to the previous case this portfolio does not have the highest beta. In case of India, the rest of portfolios do not exhibit intercept statistically significant from zero.

Table 21- Time Series Results Aggregate India

Eq Name: *Dep. Var:*	PORTFOLIO1 -RF__	_2_PORTFOL IO-RF__	_3_PORTFOL IO-RF__	_4_PORTFOL IO-RF__	_5_PORTFOL IO-RF__	_6_PORT FOLIO- RF__
C	0.093699	-0.002849	0.016535	0.016695	0.033722	0.004994
	[3.1827]**	[-0.9169]	[1.5353]	[1.4367]	[2.3782]*	[0.5598]
RM_RF__	1.089567	0.994788	0.844209	1.103819	0.861249	0.789637
	[38.5148]**	[291.4361]**	[64.1765]**	[87.1453]**	[49.3185]**	[71.1800]**

Similar results can be found in the research conducted by Black, Jensen and Scholes (1972), who argued that in this case since one can argue for non-normality of the residual distribution, the “t” statistic should be referenced with caution. Furthermore, based on the assumption that there is some non-stationarity in the relations these results can understate the departures from the traditional model. Therefore, to account for these limitations the researcher has sub-divided the data into sub-samples as follows:

Table 22- Sub-periods Description

Period	Periods for US stocks	Periods for Indian stocks
1	1926M07 1941M12	1993M1 1998M12
2	1942M01 1957M12	1999M1 2004M12
3	1958M01 1973M12	2005M1 2010M12
4	1974M01 1989M12	2011M1 2016M11
5	1990M01 2005M12	
6	2006M01 2016M12	

The results for Portfolio 1 below confirm the original hypothesis of this paper. Firstly, one can see that alpha coefficients are non-stationary. At the start of the sample, the coefficient has positive sign and at the most current period the coefficient changes the sign to negative. We can also see that during 2 out of 5 sub-periods intercept is statistically different from zero. Furthermore, in the last period portfolio has negative intercept, the beta is the highest out of all, which contradicts the main assumption of the traditional CAPM model.

Table 23 - Results for the Alpha Portfolio 1 US

Eq Name:	**Period 1**	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**
Dep. Var:			_1_PORTFOLIO-RF			
C	0.111558	0.113347	0.383420	0.380001	0.222373	-0.176393
	[0.3141]	[0.6969]	[2.8853]**	[2.6552]**	[1.1717]	[-0.8460]
Beta Coefficient	1.435695	1.226259	1.036408	0.862635	0.855967	1.229180
	[17.7312]**	[29.4519]**	[29.8955]**	[30.0232]**	[19.3786]**	[25.8699]**

If these results would be compared to the Indian stocks, we can see similar trend the coefficient in the last period is statistically different from zero, furthermore it is negative and we can also see the highest beta in comparison to other sub-periods.

Table 24- Aggregate Results for Alpha Portfolio 1 India

Eq Name:	**Period 1**	**Period 2**	**Period 3**	**Period 4**
Dep. Var:		**PORTFOLIO1**		
C	0.008113	0.032456	0.422449	-0.076575
	[0.1497]	[0.3985]	[9.5402]**	[-1.9651]*

Beta Coefficient	1.312451	0.957022	0.902390	1.719449
	[24.8693]**	[15.2578]**	[22.7046]**	[38.6329]**

Looking at all portfolios (see appendix), the divergence of the intercept from zero is common for the riskiest portfolio 5 and for portfolio 1 that we have considered. For other portfolios, one can see that the relationship is not stationary, that at some points in sub-samples there is a change in sign and the intercept is significantly different from zero. What is also important to consider is the variation of beta coefficient. As one can see in case of Indian Portfolio 1, beta is non-constant the same can be seen case of US portfolio 1. This breaks one of the main assumptions of unconditional CAPM.

One can also look at the problem from a different perspective, by considering six portfolios through different sub-periods. The most volatile period for US portfolios is period four. During this period, four outs of six portfolios have intercepts significantly different from zero. One can also see increasing trend over time, where portfolios started earning more and more unexpected returns during the most recent periods. A common trend shared by most of the portfolios is the negative alpha at the last period. During this period, majority of the portfolios also have the highest betas. This can be attributed to effects of crises.

Table 25- Period 4 Alpha Results US

Eq Name:			**Period 4**			
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.380001	-0.191621	0.549148	0.145643	0.775089	0.005107
	[2.8291]**	[-2.1682]*	[3.1000]**	[1.7292]	[3.6269]**	[0.0258]
Beta Coefficient	0.862635	1.060837	1.025579	0.921020	0.989907	1.273659
	[18.8554]**	[38.6030]**	[15.2078]**	[34.5036]**	[12.1244]**	[23.2301]**

Looking at Indian portfolios, the most volatile is period two (1999-2004), when three out of six portfolios have positive statistically different from zero intercepts. This can be attributed to economic boom during this times.

Table 26 - - Indian Portfolios Period 2

Eq Name:			**Period 2**			
Dep. Var:	PORTFOLIO 1-RF__	_2_PORTFOLIO-RF__	_3_PORTFOLIO-RF__	_4_PORTFOLIO-RF__	_5_PORTFOLIO-RF__	_6_PORTFOLIO -RF__
C	0.032456	-0.001067	0.073586	0.075539	0.109355	0.012925

	[0.3985]	[-0.2864]	[3.0980]**	[2.3293]*	[3.3339]**	[0.6384]
Beta Coefficient	0.957022 [15.2578]**	0.945347 [177.4908]**	0.767625 [40.5798]**	0.982330 [32.2587]**	0.825032 [33.8059]**	0.781372 [56.1879]**

Considering all the periods (see appendix) one can observe that generally only positive intercepts are statistically different from zero. Another important result that should be mentioned is that beta coefficients are non-constant. One of the main claims of unconditional beta models such as traditional CAPM and consequently all of it modifications including the three-factor model is the assumption that beta coefficient does not evolve through time. It is evident from the above results that all the beta coefficients are statistically significant and since they are changing through time for all of the portfolios. Thus, it can be concluded that this condition is violated. This finding is consistent with various researches that put forward arguments of non-constant volatility, which results into time-varying covariances and consequently alters the calculation of beta. For the future research, it thus should be relevant to talk about conditional downside beta calculations rather than unconditional D-CAPM.

To summarize above mentioned, one could confirm the hypothesis that the coefficients are non-constant and there is non-stationarity present. Furthermore, it can be said that in many instances portfolios had positive statistically different from zero intercepts, which contradicts the main assumption of traditional CAPM. However, in general, the results are inconclusive in regards to complete rejection of the null hypothesis (that the intercept is equal to zero) and the author can cannot confirm her assumption about negative intercepts and higher beta relationships, as it was present only in case of portfolio 1 for India.

6.3.3 Traditional CAPM Testing

In this section, we are going to look at the testing of the models from a different perspective of portfolios. As per various research, portfolios are better representation of investor choice. The first part of the analysis will look at the variation in the excess returns and their association with the risk measures from two models – (1) traditional CAPM and (2) DCAPM.

In the table below, one can see the results from simple regression of excess monthly returns of US portfolios on market premium (see detailed tables in the Appendix). It is clear from the results that all the relationships are statistically significant and have high explanatory power (R-squared).

Table 27- CAPM and Mean Excess Returns US

Portfolio	Mean Returns	Beta	Beta FF
1	0.92	1.21	1.09
2	0.63	0.97	1.02
3	0.99	1.19	0.98
4	0.69	1.01	0.99
5	1.20	1.32	1.02
6	0.69	1.26	1.09

The highest beta is assigned to the highest return (portfolio 5), which confirms the general relationship between risk-return, since as has been mentioned previously portfolio 5 is the riskiest portfolio out of the set. However, for the rest of portfolios beta does not show such clear-cut differences. For instance, if we consider portfolio 6, which has one of the lowest returns, the beta is second highest. To check the results, the author ran another regression of mean excess return on beta. The results can be seen in Table 28.

Table 28 - Second Step Regression Beta Mean Returns US

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.511134	0.262738	-1.945409	0.1236
BETA	1.174410	0.267149	4.396082	0.0117

R-squared	0.551642	Mean dependent var	0.851436
Adjusted R-squared	0.439552	S.D. dependent var	0.222157
S.E. of regression	0.166313	Sum squared resid	0.110640
Durbin-Watson stat	2.015953	J-statistic	6.28E-43
Instrument rank	2		

As can be seen the relationship is significant and R-squared is quite high. The model explains approximately 55% of the change in mean excess returns. However, based on the Cook’s Distance there is one outlier portfolio 6. Once this observation is removed and another second-step regression is performed, we get even better results, with approximately 96% of the variations in mean returns being explained by beta (Table 30).

Figure 12 - Beta against Mean Returns Plot 6 US Portfolios

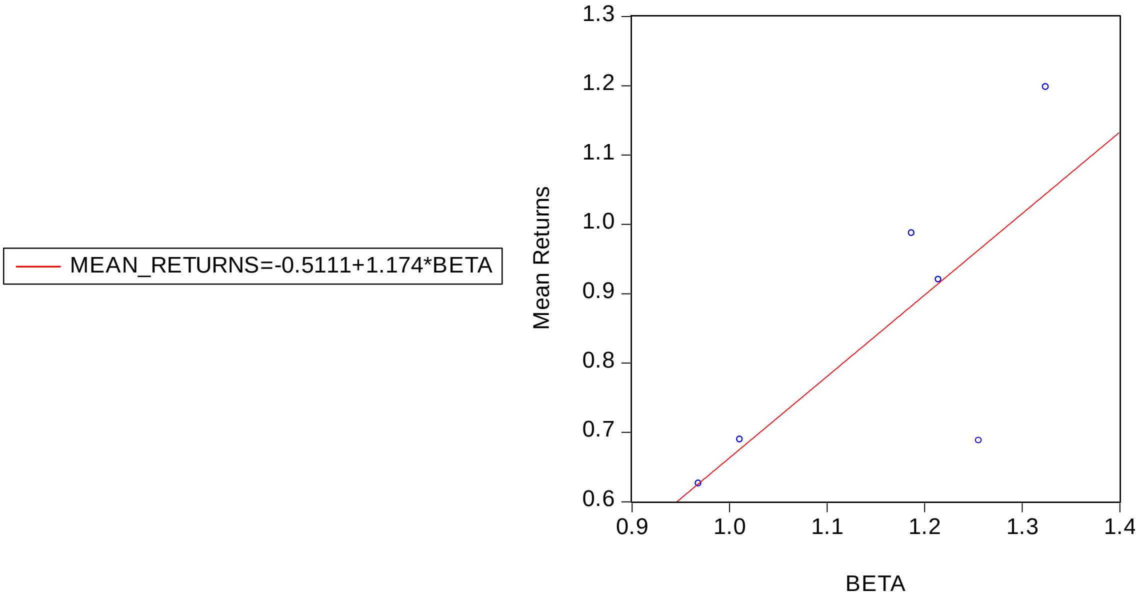


Table 29- Beta against Mean Returns 6 US Portfolios without outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.886593	0.125490	-7.065049	0.0058
BETA	1.554907	0.126684	12.27392	0.0012

R-squared	0.964749	Mean dependent var	0.886000
Adjusted R-squared	0.952999	S.D. dependent var	0.231582
S.E. of regression	0.050206	Sum squared resid	0.007562
Durbin-Watson stat	1.114418	J-statistic	0.000000
Instrument rank	2		

To test CAPM further it makes sense to add extra variables such as value and size suggested by Fama and French (1992), re-estimate beta to check if beta it is still significant, and explains the same portion of returns. New beta coefficients can be found below (Table 29). If we would plot new beta against mean returns, we would see that the relationship became nearly flat with negative inclination. In this case, there is no evident outlier identified both through z-score and boxplots, thus the relationship can be defined as insignificant.

Figure 13 - Beta FF against Mean Return Plot US 6 Portfolios

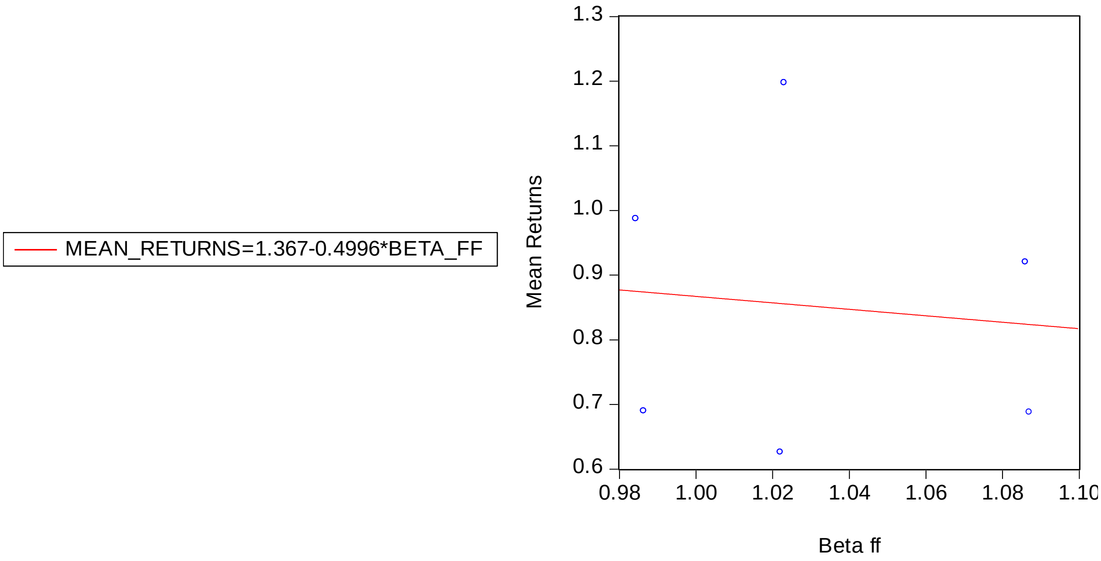


Table 30 - Second Step Regression Beta FF against Mean Returns US Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.366765	1.195323	1.143427	0.3166
BETA_FF	-0.499620	1.135669	-0.439934	0.6827
R-squared	0.010602	Mean dependent var		0.851436
Adjusted R-squared	-0.236748	S.D. dependent var		0.222157
S.E. of regression	0.247058	Sum squared resid		0.244151
Durbin-Watson stat	3.345500	J-statistic		0.000000
Instrument rank	2			

However, to ensure correctness of the result it is advisable to increase the number of observations in the second-step regression. In case of US, it is possible to obtain 25 portfolios formed on Size and Value from French Data Library. Similarly, to previous analysis the two-steps regression was performed with the necessary adjustments for autocorrelation and non-constant variance of the residuals. The results for the first step-regression can be found in Table 32.

Table 31 - 25 US portfolios Beta and Beta FF results

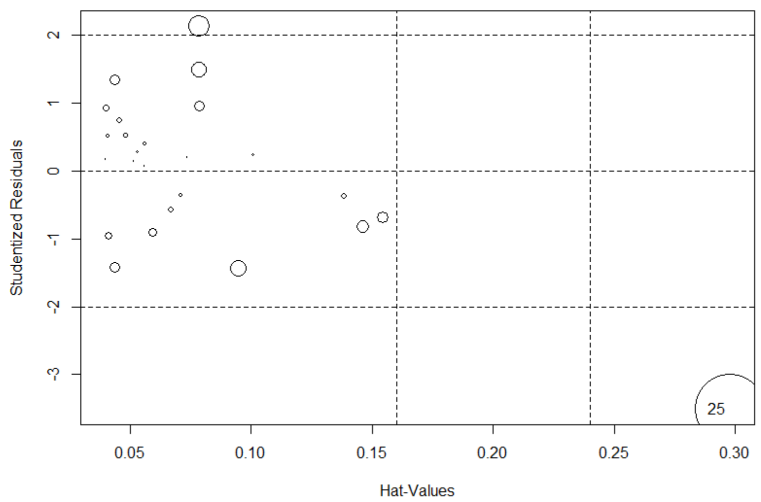
Portfolios	Mean Returns	Beta	Beta FF
1	0.96	1.31	1.18
2	0.61	0.96	1.02
3	0.69	1.41	1.08
4	1.00	1.37	1.05
5	1.19	1.27	0.95
6	0.62	1.27	1.09
7	0.93	1.23	1.02
8	0.99	1.20	0.98

9	1.08	1.21	0.97
10	1.26	1.38	1.07
11	0.70	1.25	1.13
12	0.91	1.13	1.02
13	0.93	1.12	0.99
14	1.02	1.16	0.98
15	1.16	1.38	1.13
16	0.71	1.09	1.08
17	0.75	1.08	1.02
18	0.86	1.12	1.02
19	0.97	1.15	1.03
20	1.03	1.42	1.22
21	0.63	0.95	0.99
22	0.70	0.97	0.96
23	0.65	1.11	1.04
24	1.37	1.38	0.99
25	0.56	1.63	1.29

**All of the parameter estimates are statistically significant*

To identify outliers in this section the author firstly used a labelling rule as in previous examples however this approach has not identified any outliers and the relationship was insignificant. The author then used Z-score approach and the coefficient of the 25th portfolio has been identified as an outlier based on having a z-score higher than 2. This has also been confirmed by the Cook's distance test (see Figure 14).

Figure 14 - Cook's Distance test US 25 Portfolios



Thus, it was excluded from the second-step regression. Graphical representation of relationship between beta and mean excess returns can be seen in Figure 15. The slope of the relationship is quite steep, indicating that beta has discriminatory power between high and low mean returns.

Figure 15 - 25 US portfolios Beta - Mean Return Relationship

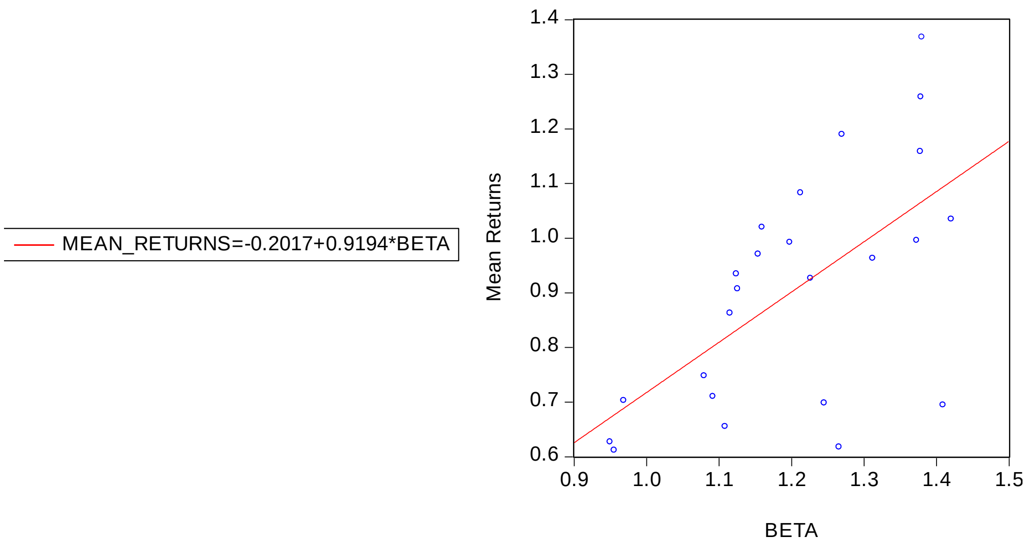
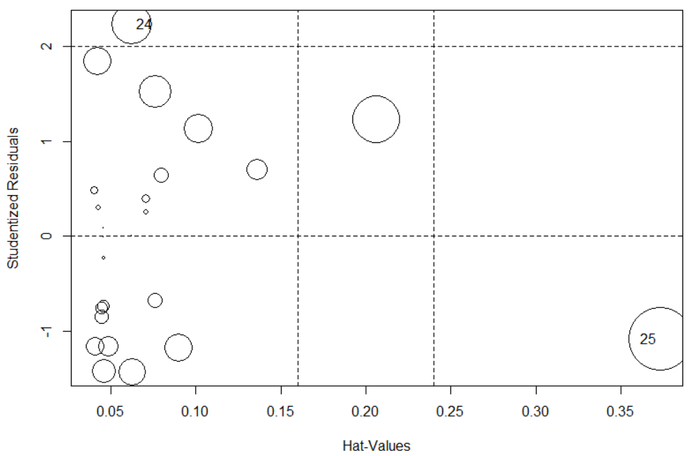


Figure 16 - Beta FF outlier Identification 25 US Portfolios



Beta coefficient is still significant and has a positive relationship with the mean returns as is suggested by the traditional CAPM model, however r-squared has decreased from 55% to just 37%. This result is closer to what has been estimated in past papers. To account for size and value effect, the author has re-estimated the beta coefficient with adding extra factor as in case of 6 portfolios (see Table 32). Portfolio 25 and 24 were identified as outliers based on boxplot method and Cook's Distance and were removed from the analysis. However, removing these portfolios from the data set this time did not change the relationship between the beta and mean returns to positive and significant (see Figure 17).

Table 32 - US 25 Portfolios Beta-Mean Returns Relationship

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-0.201719	0.269659	-0.748054	0.4624
BETA	0.919440	0.239372	3.841045	0.0009

R-squared	0.374785	Mean dependent var	0.905412
Adjusted R-squared	0.346366	S.D. dependent var	0.215876
S.E. of regression	0.174531	Sum squared resid	0.670142
Durbin-Watson stat	2.084285	J-statistic	3.50E-45
Instrument rank	2		

The relationship remained quite flat, showing that beta is not able to diversify between low returns and high returns. Furthermore, it is evident from the graph that the relationship is negatively inclined, which contradicts to the main assumption of the traditional CAPM model. These findings are further confirmed by the second step regression (Table 34).

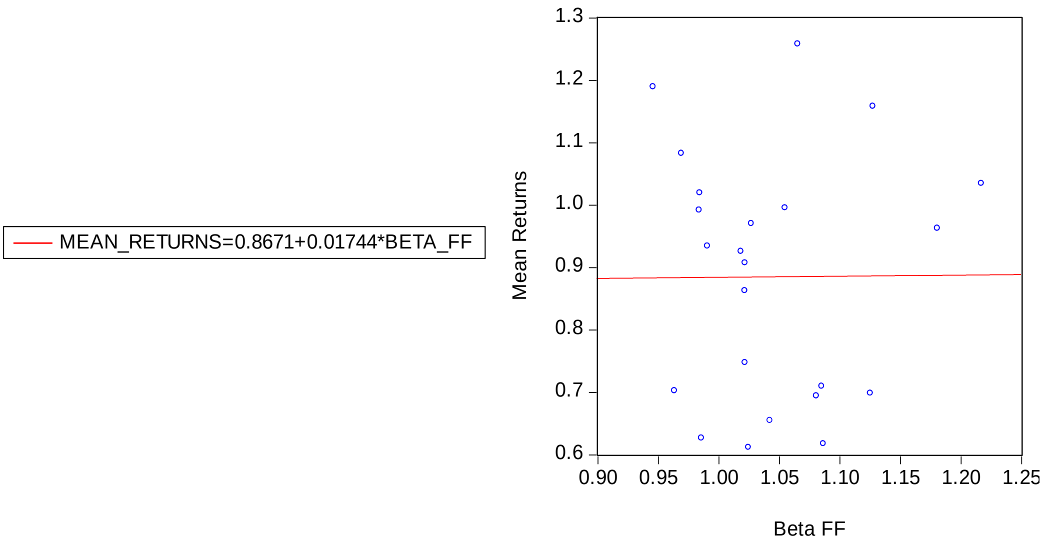
Table 33 - Second-step regression Beta FF against Mean Returns 25 US Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.867086	0.728534	1.190180	0.2473
BETA_FF	0.017444	0.679753	0.025663	0.9798

R-squared	0.000038	Mean dependent var	0.885305
Adjusted R-squared	-0.047579	S.D. dependent var	0.196410
S.E. of regression	0.201028	Sum squared resid	0.848658
Durbin-Watson stat	1.783845	J-statistic	5.90E-43
Instrument rank	2		

The main explanation to such results can be attributed to the problem of specification bias, where if the model omits some significant variables the beta coefficient is biased by including the effects of other variables. In this case, effect of size and value. Thus, in case of portfolios originating from the US, one can confirm that specification bias was present when the two factors are not included into the regression equation. This confirms research findings of the Fama-French (1992).

Figure 17 - Beta FF against Mean Returns Plot 25 US Portfolios without outlier



To make sure that similar results hold in other developed markets, the author decided to include 6 and 25 portfolios for Asia Pacific (includes Australia, Hong Kong, New Zealand and Singapore). The results for mean returns and respective beta coefficients in case of both traditional beta and beta with Fama-French factors can be seen in the Table 35.

Table 34 - Asia Pacific 6 Portfolios Beta and Beta FF

Portfolios	Mean Return	Beta	Beta FF
1	1.003	1.12	1.07
2	0.60	0.97	1.00
3	0.57	1.02	1.02
4	0.70	0.97	0.97
5	0.99	1.00	0.97
6	0.10	1.03	1.05

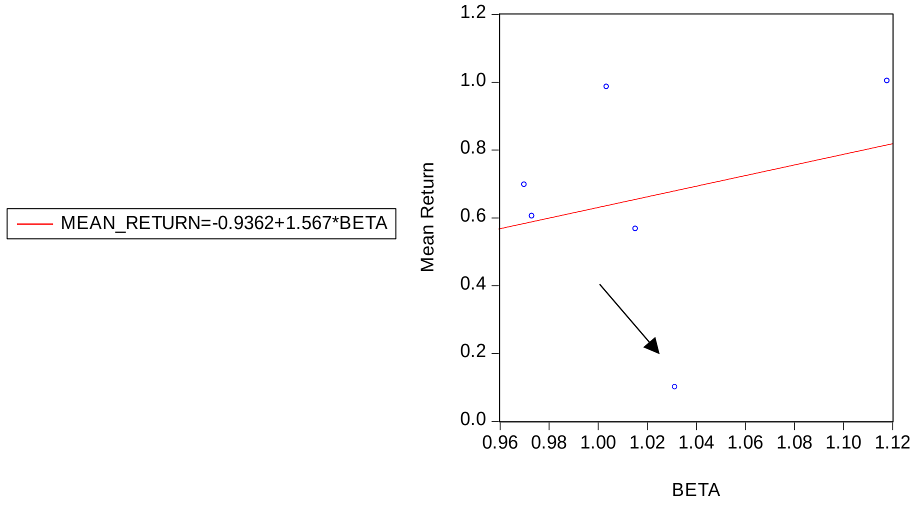
If we plot the traditional beta against mean returns, we can see that there is one outlier in the relationship (see Figure 18) before removing this outlier the relationship between mean returns and beta is insignificant (Table 36).

Table 35 - Second Step Regression Asia Pacific 6 Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.936155	1.978661	-0.473126	0.6608
BETA	1.566951	1.981621	0.790742	0.4733

R-squared	0.065527	Mean dependent var	0.659771
Adjusted R-squared	-0.168091	S.D. dependent var	0.331817
S.E. of regression	0.358622	Sum squared resid	0.514438
Durbin-Watson stat	1.944682	J-statistic	0.000000
Instrument rank	2		

Figure 18 - Asia Pacific 6 Portfolios Beta against Mean Returns Plot



Removing the outlier results in more precise feet and thus if we look at the second-step regression we can see that the relationship became significant and r-squared is approximately 39.5%, adjusted r-squared is just 19.36% which mean that the model will be much less powerful in making predictions.

Figure 19- Asia Pacific 6 Portfolios Beta against Mean Returns without Outlier

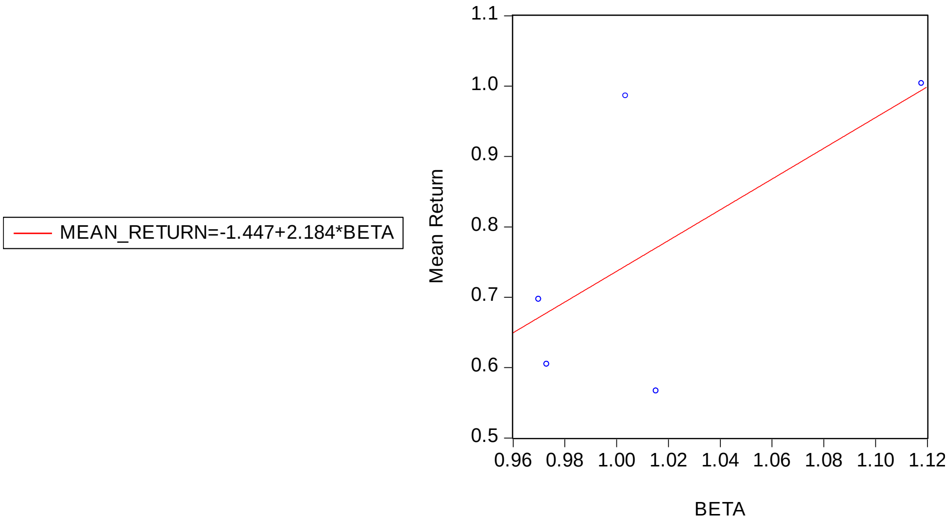


Table 36 - Second Step Regression Asia Pacific 6 Portfolios without Outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.447367	0.541402	-2.673368	0.0755
BETA	2.184253	0.466649	4.680722	0.0184

R-squared	0.395210	Mean dependent var	0.771656
Adjusted R-squared	0.193614	S.D. dependent var	0.209142
S.E. of regression	0.187807	Sum squared resid	0.105815
Durbin-Watson stat	1.160439	J-statistic	3.22E-44
Instrument rank	2		

To check if beta remains significant one could also add more explanatory factors and see if beta keeps its power. In this case, we return to 3 factors suggested by Fama and French (1992), running a new set of regressions to estimate the Beta FF. When plotting original relationship we can see that it is flat and negatively inclined, there are also outliers. Based on Cook's distance portfolio 1 should be removed. Once this observation is removed the relationship becomes between Beta FF and Mean Returns becomes steeper but negative (see Figure 21).

Figure 20 – Beta FF against Mean Returns Asia Pacific 6 Portfolios (with outlier identification)

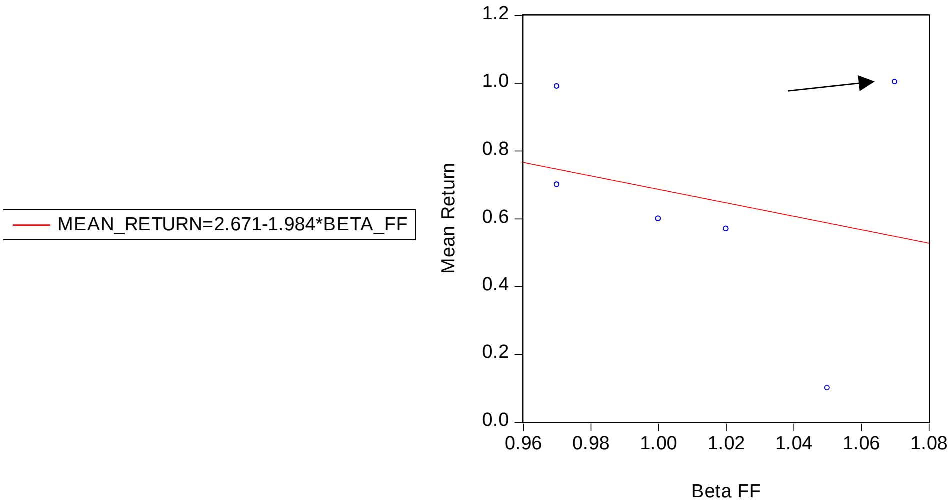
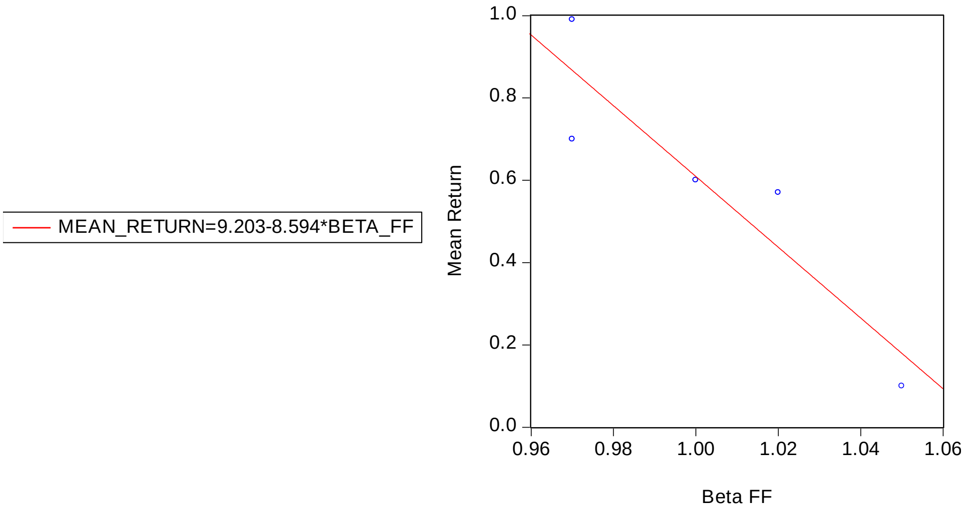
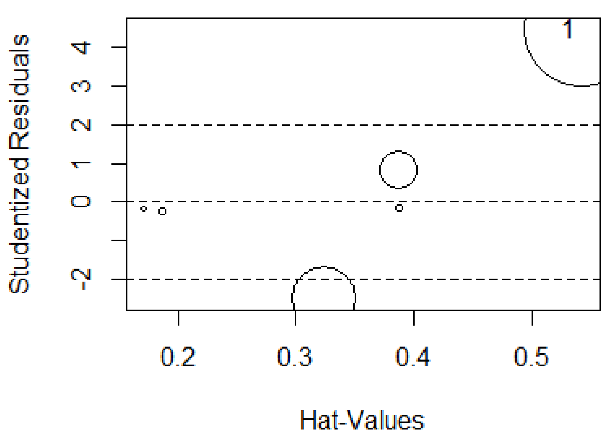


Figure 21 - Asia Pacific 6 Portfolios Beta FF against Mean Returns without outlier





Looking at the second-step regression one can see that beta is significant at 5% level. However, the relationship is negative, which contradicts the main assumption of traditional CAPM model. Thus, one cannot confirm that the model has successfully passed the test for specification bias. Furthermore, one can argue that once size and value effects have been removed the relationship has changed and if the model is used without these factors it can yield biased results.

Table 37 - Second Step Regression Asia Pacific 6 Portfolios Beta FF against Mean Returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.203205	2.016788	4.563299	0.0197
BETA_FF	-8.594017	2.019077	-4.256410	0.0238

R-squared	0.837577	Mean dependent var	0.592000
Adjusted R-squared	0.783436	S.D. dependent var	0.321201
S.E. of regression	0.149475	Sum squared resid	0.067029
Durbin-Watson stat	3.506684	J-statistic	1.06E-41
Instrument rank	2		

It is though evident that small sample testing can offer distorted results. To further check the relationship between the beta and mean returns, it is reasonable to add more observations and see if the relationship remains as powerful as in the previous cases. The results for 25 Asia Pacific Portfolios sorted on size and value can be found in Table 38.

Table 38 - Asia Pacific 25 Portfolios CAPM Results

Portfolios	Mean excess Return	Beta	Beta FF
1	1.21	1.16	1.11
2	0.78	0.98	1.01
3	0.60	1.05	1.07
4	0.95	1.01	1.01
5	1.31	0.97	0.97
6	0.15	0.99	1.01
7	0.45	1.09	1.10
8	0.59	0.97	0.98
9	0.81	1.00	0.99
10	1.13	1.04	1.00
11	0.35	1.03	1.06
12	0.51	1.01	1.03
13	0.96	1.01	1.02
14	0.95	1.01	1.00
15	0.99	1.07	1.03
16	0.78	0.97	0.99
17	1.02	0.93	0.94
18	0.78	0.96	0.97
19	1.03	1.00	1.00
20	1.23	1.17	1.13
21	0.96	0.98	0.99
22	1.04	0.99	0.99
23	0.97	0.98	0.96

24	1.68	0.93	0.91
25	0.71	1.03	1.06

Before running first-step regression, the results were checked on outliers and after gradually removing 4 observations that exhibited high Z-scores and Cook distance (portfolios 5, 6, 15 and 18), one can see positive relationship (see Figure 22). Second-step regression confirms significance of the model and coefficient of determination shows that beta can explain approximately 16.7% of changes in returns. This is much weaker result than in case of US, however still reasonable given the data set at hand.

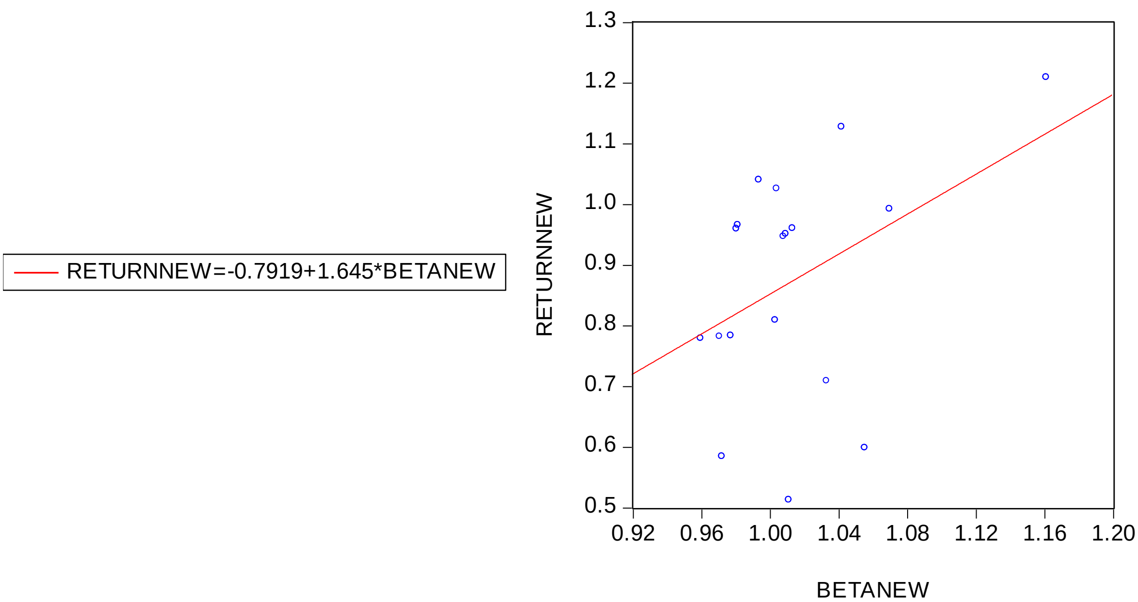
Table 39 - Asia Pacific Beta-Mean Return Relationship

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.791882	0.673853	-1.175155	0.2571
BETANEW	1.644818	0.671650	2.448921	0.0262

R-squared	0.166886	Mean dependent var	0.874792
Adjusted R-squared	0.114817	S.D. dependent var	0.191465
S.E. of regression	0.180138	Akaike info criterion	-0.485748
Sum squared resid	0.519195	Schwarz criterion	-0.386817
Log likelihood	6.371729	Hannan-Quinn criter.	-0.472106
F-statistic	3.205066	Durbin-Watson stat	2.461752
Prob(F-statistic)	0.092350	Wald F-statistic	5.997213
Prob(Wald F-statistic)	0.026229		

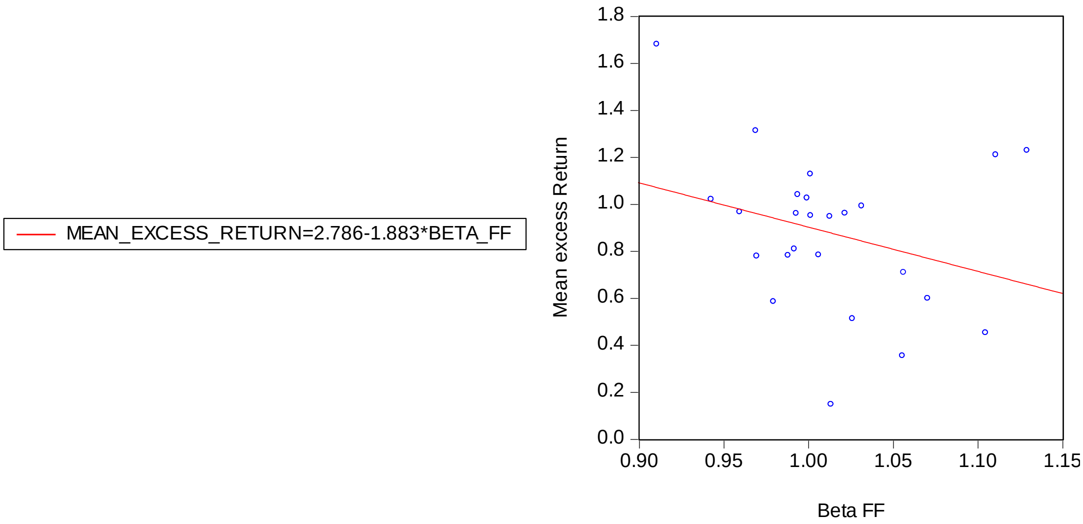
Figure 22 - Asia Pacific Beta- Mean Return Relationship



Since all the markets included into Asia Pacific portfolios are considered to be developed, these results show that not all of the advanced economies possess the same characteristics.

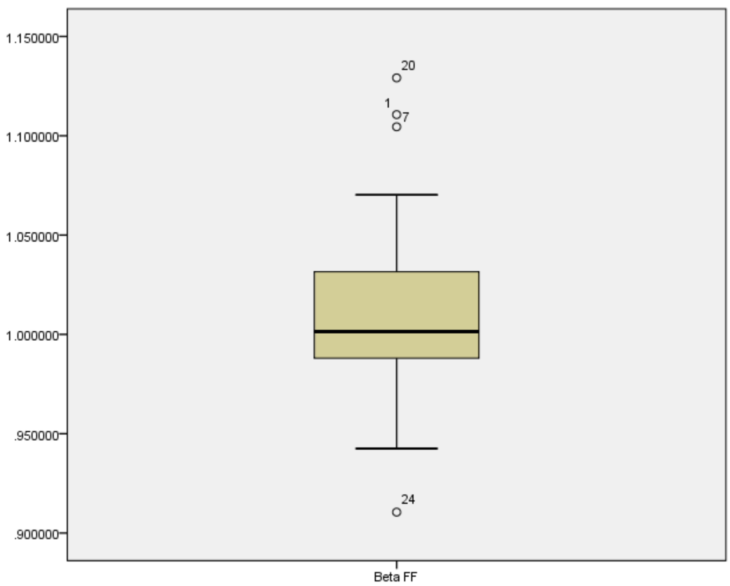
Thus, when performing valuations or pricing of assets in these markets caution must be paid and one cannot blindly apply traditional asset pricing models. Similarly, to US testing, the author has run the first-step regression again with extra factors to check if beta power remains the same, the results for Beta FF, can be found in Table 38. The original plot of the relationship has shown negative association between beta and mean returns (see Figure 23).

Figure 23- Beta FF against Mean Returns 25 Asia Pacific Portfolios Plot



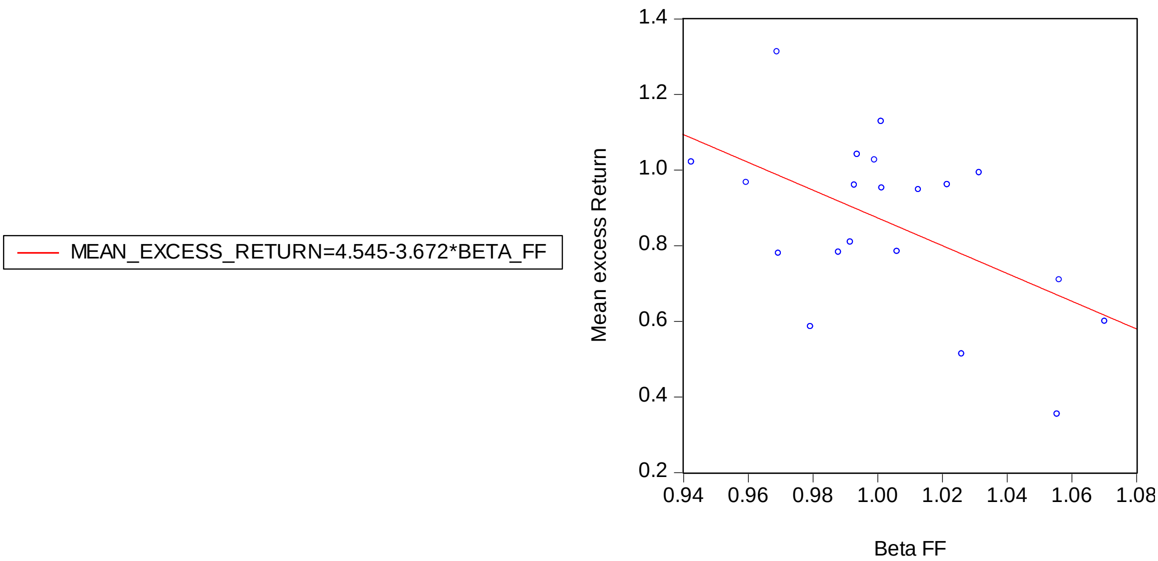
However, several outliers (portfolio 1, 7, 20 and 24) and confirmed by all of the methods (Z-score, Cook’s distance, box plots and scatter plot).

Figure 24 - Beta FF Asia Pacific 25 Portfolios Outlier Identification



After removing these outliers, the relationship became significantly negative as in case of 6 portfolios. This time the regression line is no longer flat as in case of US, so beta does diversify between the high return and the low return. However, the relationship is the opposite of the one suggested in the original paper. Furthermore, this time one cannot argue that this has been caused by negative return as all the portfolios have positive mean returns (see Figure 25).

Figure 25 - Beta FF against Mean Returns Plot 25 Asia Pacific Portfolios without Outliers



Consequently, one can see that second-step regression confirms the significance of beta relationship with the mean returns and its negative slope. We can also see that the model explains approximately 28.38% of the movements in the mean returns, which is much lower than in case of 6 portfolios, but more realistic. From this, we can conclude that the model generally does not hold even though the relationship is statistically significant.

Table 40 - Second Step Regression Beta FF against Mean Returns 25 Asia Pacific Portfolios without outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.545432	1.454055	3.126040	0.0058
BETA_FF	-3.671807	1.445443	-2.540264	0.0205

R-squared	0.283867	Mean dependent var	0.861197
Adjusted R-squared	0.244082	S.D. dependent var	0.228388
S.E. of regression	0.198569	Sum squared resid	0.709731
Durbin-Watson stat	1.899062	J-statistic	3.92E-44
Instrument rank	2		

The results for Indian portfolios also follow a trend of weak association between beta and mean returns. We can see that the highest beta is assigned to the lowest return (portfolio 1) whereas the highest excess return (portfolio 5) is given beta lower than one. In Figure 26, one can see a plot of the relationship between traditional beta and mean returns.

Table 41 - Beta/Beta FF and Mean Returns India

Portfolio	Mean Returns	Beta	Beta FF
1	0.42	1.17	1.02
2	0.55	0.96	0.99
3	0.86	1.08	0.98
4	1.02	1.05	1.00
5	1.22	1.16	0.98
6	0.59	1.00	0.95

As one can see the relationship is positive, however if we look at the results of the second-step regression of mean excess returns against the estimated beta coefficient, the beta coefficient is insignificant and r-squared is equal to zero. This confirms previous studies performed by Harvey (1995) that show that in emerging markets there is no relationship between beta and return. However, based on Cook's distance portfolio 1 and 2 were identified as outliers. Once the outlier is removed, the line fits the data more precisely. As the result, one can expect higher coefficient of determination and statistical significance.

Figure 26 - Indian Portfolios Beta and Return Relationship

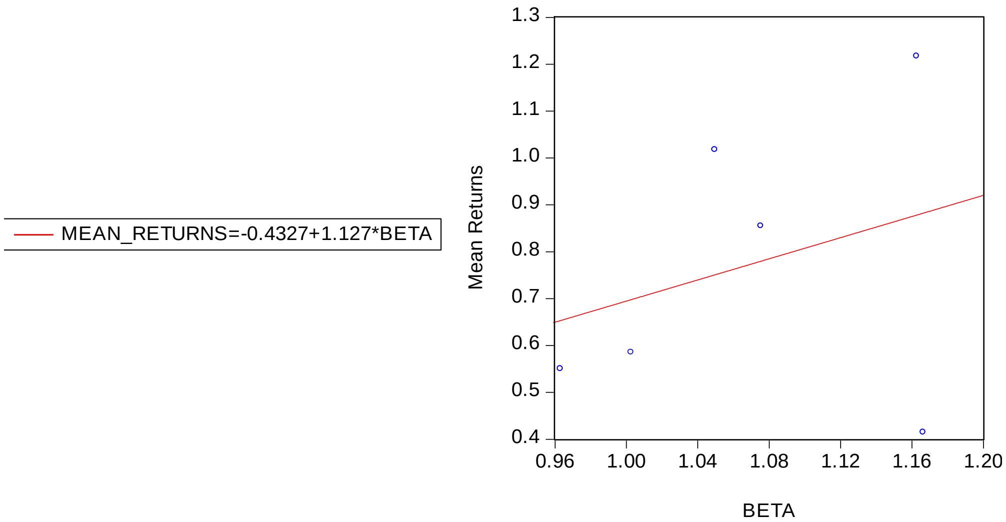
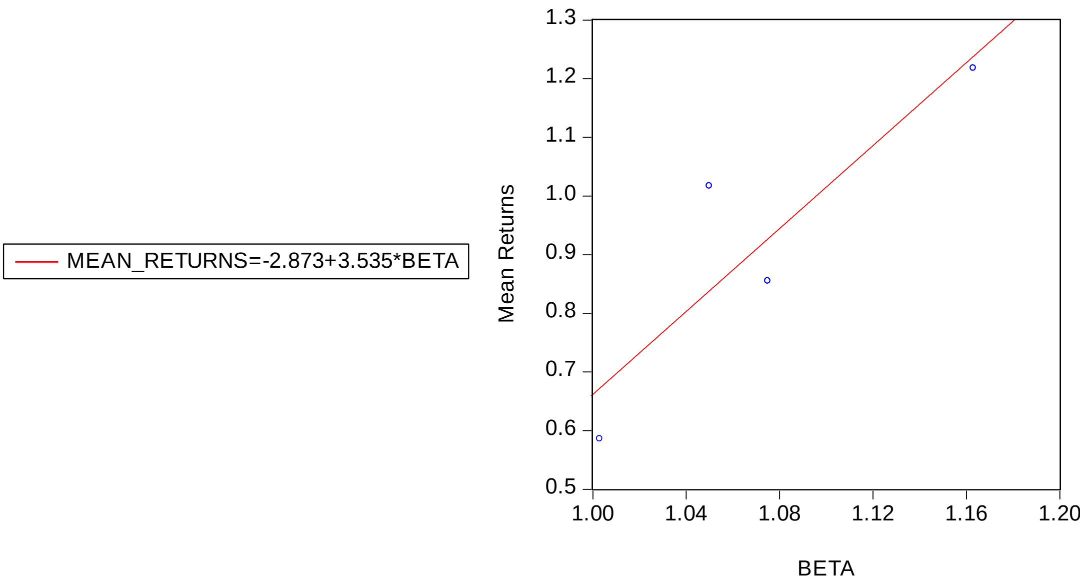


Table 42 - Second Step Regression Beta - Mean Returns 6 Indian Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.432651	1.808089	-0.239286	0.8226
Lambda1	1.127405	1.815278	0.621065	0.5682

R-squared	0.091495	Mean dependent var	0.773578
Adjusted R-squared	-0.135631	S.D. dependent var	0.308780
S.E. of regression	0.329054	Sum squared resid	0.433107
Durbin-Watson stat	0.947042	J-statistic	6.66E-44
Instrument rank	2		

Figure 27 - Beta against Mean Returns Plot 6 Indian Portfolios without Outliers



This assumption is confirmed by the second step regression (Table 43). The relationship between beta and returns is statistically significant and explains approximately 79% of the variations of the mean returns. Though it is crucial to notice that the intercept is statistically different from zero at 10% level, which breaks one of the main assumptions of traditional CAPM, which postulates that there should not be any extra/scarcity returns that are not explained by the beta coefficient.

Figure 28- Beta FF and Mean Returns Indian 6 Portfolios Plot

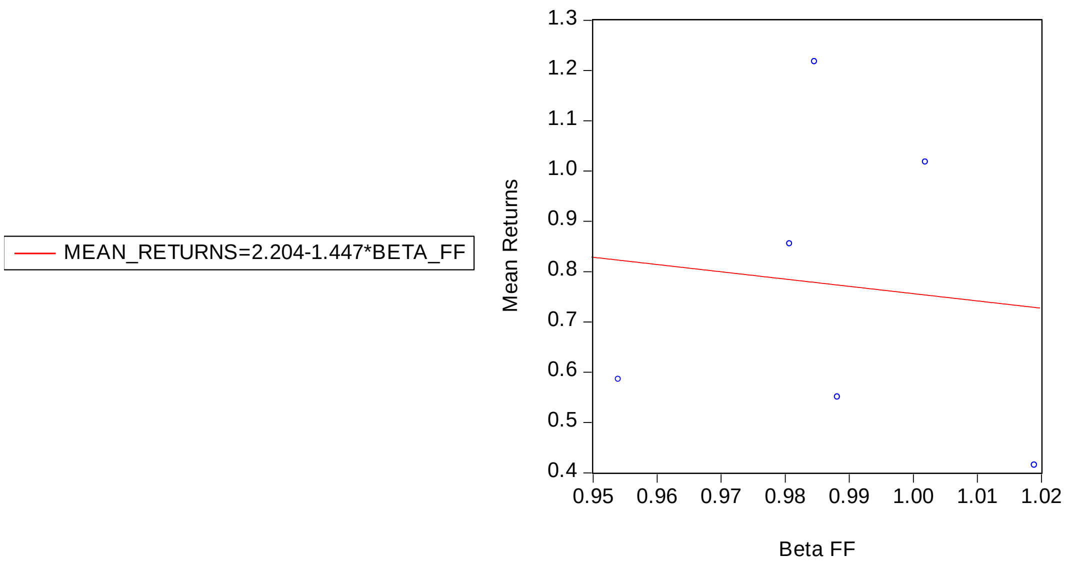


Table 43 - Second Step Regression Beta - Mean Returns 6 Indian Portfolios without outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.873150	0.874755	-3.284518	0.0815
BETA	3.534980	0.762327	4.637094	0.0435

R-squared	0.790254	Mean dependent var	0.919000
Adjusted R-squared	0.685380	S.D. dependent var	0.267077
S.E. of regression	0.149806	Sum squared resid	0.044884
Durbin-Watson stat	2.372363	J-statistic	2.15E-42
Instrument rank	2		

For further testing, extra explanatory variables (factors) were introduced to the regression, more specifically SMB and HML (Fama and French, 1992). Since our portfolios are constructed based on Size and Value adding these factors would help to remove some of the effects of size and value from beta and allow to examine if beta will still be significant. New beta (Beta FF) coefficients can be seen in the Table 41 above. All of them are statistically significant. If we plot the relationship between new beta coefficients and mean returns, one can see that spread between the points has increased and the regression line is nearly flat (Figure 28). However, this can be justified by one outlier in representation of portfolio six (see Figure 29). If this observation is removed, the relationship becomes negative. Furthermore, running a second-step regression shows that beta is no longer significant at 5% level, only at 10%. This confirms previous findings of Fama and French (1992), where the authors argue that once the size and value effects are removed from beta the relationship becomes flat.

Figure 29 - Cook's Distance 6 Indian Portfolios Beta FF

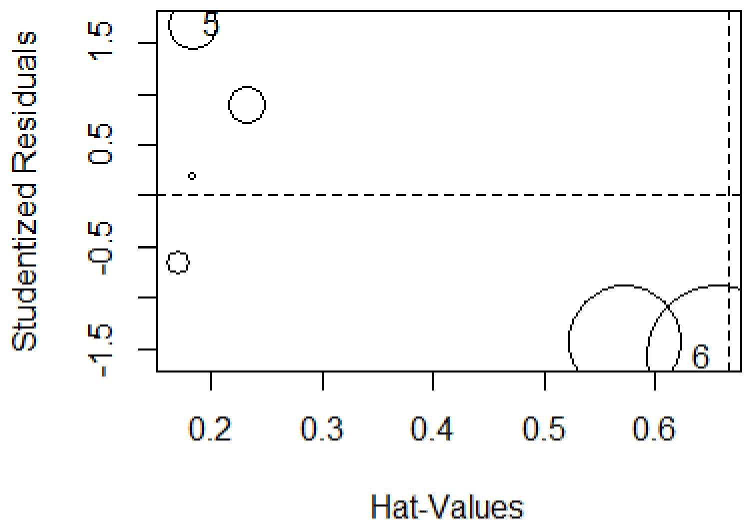


Figure 30 - Beta FF and Mean Returns Indian 6 Portfolios Plot without outlier

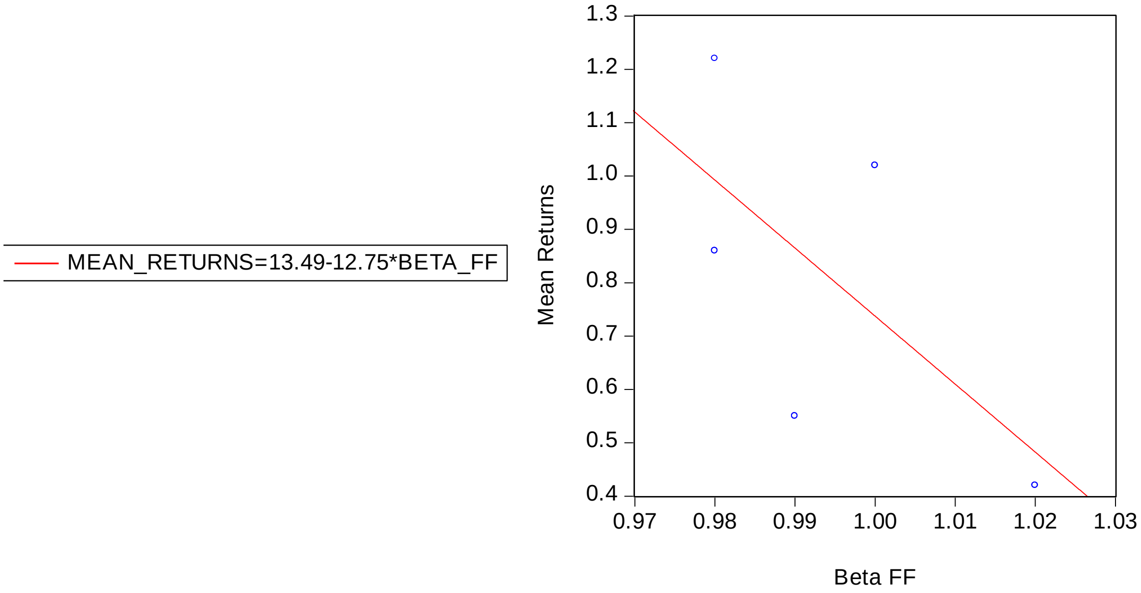


Table 44 - Second Step Regression Beta FF and Mean Returns Indian 6 Portfolios without outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.48750	4.280494	3.150922	0.0512
BETA_FF	-12.75000	4.241860	-3.005757	0.0574

R-squared	0.419207	Mean dependent var	0.814000
Adjusted R-squared	0.225609	S.D. dependent var	0.329515
S.E. of regression	0.289971	Sum squared resid	0.252250
Durbin-Watson stat	1.079534	J-statistic	1.07E-41
Instrument rank	2		

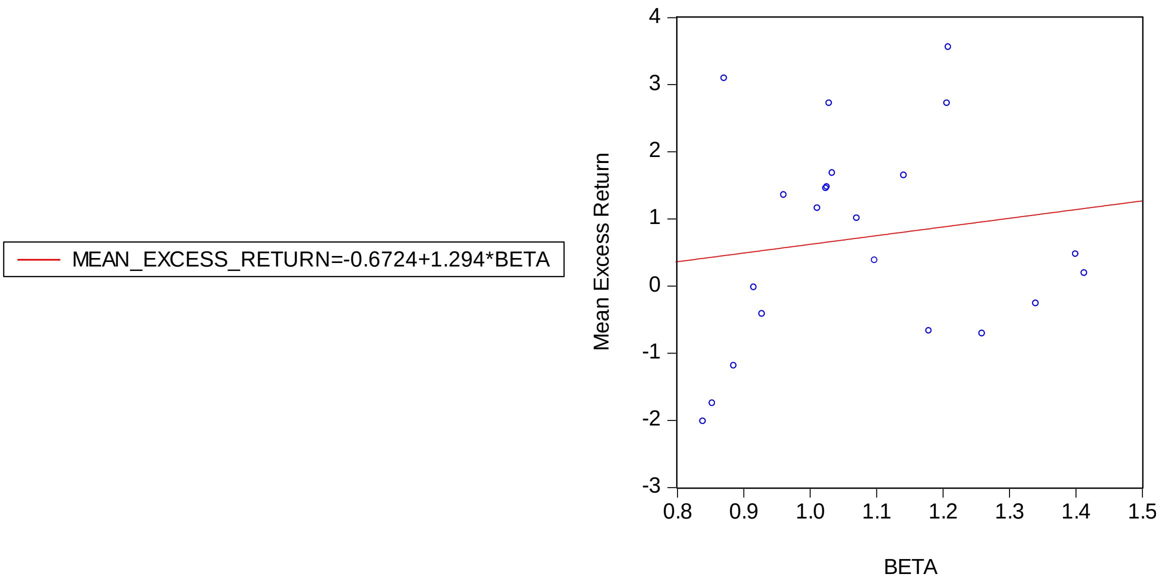
Of course, one should be cautious about making such an assertion based on regression of six portfolios and ideally should include more observations into the sample. Due to the lack of data availability this research could only perform similar calculations on segregated data (divided into 4 equal periods used in section for Time Series Testing), which as the result gave the following relationship.

Table 45 - Beta and Beta FF Coefficients Indian Portfolios

Portfolio	Mean	Beta	Beta FF
1	-0.71	1.26	1.16
2	3.06	1.03	1.11
4	-1.58	1.66	0.96
5	-0.42	0.93	0.91
6	1.16	1.01	1.02
7	1.35	0.96	0.99
8	-0.02	0.92	0.97

9	-1.75	0.85	0.99
10	2.72	1.03	0.91
11	1.65	1.14	1.04
12	0.47	1.40	1.19
13	-0.67	1.18	1.13
14	3.09	0.87	0.94
15	1.68	1.03	0.99
16	-0.26	1.34	1.18
17	-2.02	0.84	0.98
18	3.56	1.21	1.02
19	2.72	1.21	0.97
20	0.19	1.41	1.00
21	-1.19	0.89	1.04
22	1.47	1.03	0.91
23	1.45	1.02	0.97
24	0.38	1.10	0.98

Figure 31 - Beta Mean Returns Plot for 23 segregated observations Indian Portfolios



Even though the relationship on the graph is positive the results of second-step regression show that, the relationship between beta and returns is insignificant at 5% and r-squared is again close to 2%, however one should adjust for outliers which in this case were identified based on z-score and Cook's distance.

Table 46 - Second Step Regression for 23 segregated observations Indian Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.672371	2.400145	-0.280138	0.7822
BETA	1.294308	2.197153	0.589084	0.5624

R-squared	0.021270	Mean dependent var	0.721368
Adjusted R-squared	-0.027666	S.D. dependent var	1.538184
S.E. of regression	1.559316	Sum squared resid	48.62934

Durbin-Watson stat	2.130837	J-statistic	0.000000
Instrument rank	2		

Figure 32 - Beta against Mean Returns Indian Portfolios without outliers

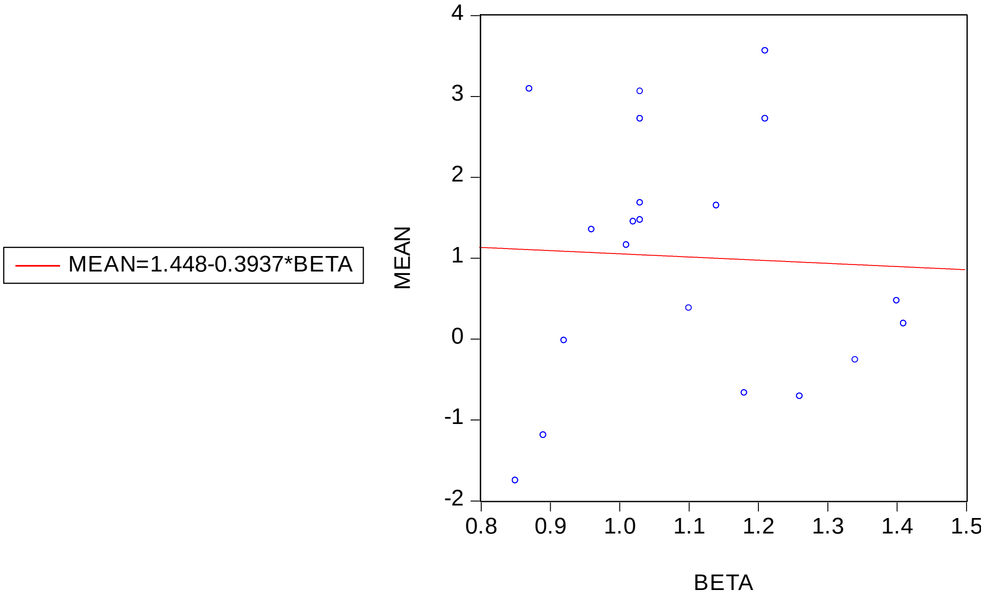
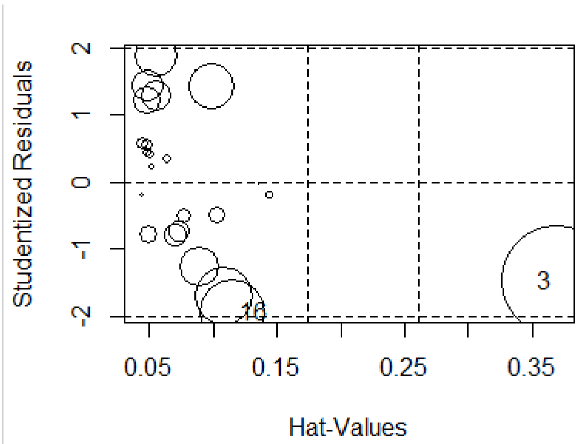


Figure 33 - Cook's distance for 25 Indian Portfolios Beta



Observations for periods 3, 16 were identified as outlier based on Cook's distance (see Figure 33) and 4 based on z-score. Once these outliers were gradually removed, the relationship becomes negative and statistically significant. One can see that this time the model explains zero of the movements in the returns and has a negative Adjusted R-squared, which is also commonly interpreted as zero.

Table 47 - Second Step Regression Beta-Mean Returns without outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.448445	2.720239	0.532470	0.6009

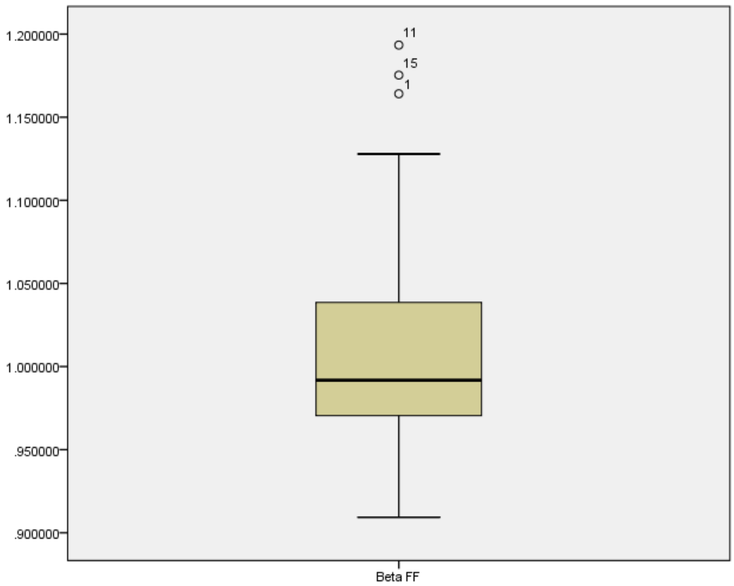
BETA	-0.393736	2.402255	-0.163903	0.8716

R-squared	0.001902	Mean dependent var	1.017500
Adjusted R-squared	-0.053548	S.D. dependent var	1.531311
S.E. of regression	1.571776	Sum squared resid	44.46865
Durbin-Watson stat	1.972592	J-statistic	0.000000
Instrument rank	2		

It is important to mention that the relationship seems to violate the main assumption of traditional Sharpe-Lintner CAPM (1964) that states that as beta increases as the returns are supposed to increase; this is similar finding to previous papers that claim that traditional beta is not applicable measure for emerging markets. These findings confirm authors hypothesis that beta is not efficient measure for emerging markets.

For further examination of this relationship, the author has recalculated beta adding extra factors (size and value). One can see plot of the new relationship below with outliers removed based on the labelling rule (Figure 34) and Cook's distance.

Figure 34 - Beta FF Indian Portfolios Outlier Identification



As one can see from the plot, the relationship is similar to the ones we have seen previously. One of the main characteristics again is its flatness, which shows that beta does not have explanatory power in determining whether returns are high or not. Furthermore, residuals are quite high as the data points are spread quite far from the fitted line. This is confirmed by second-step regression, which shows insignificance of beta as a risk measure (Table 47).

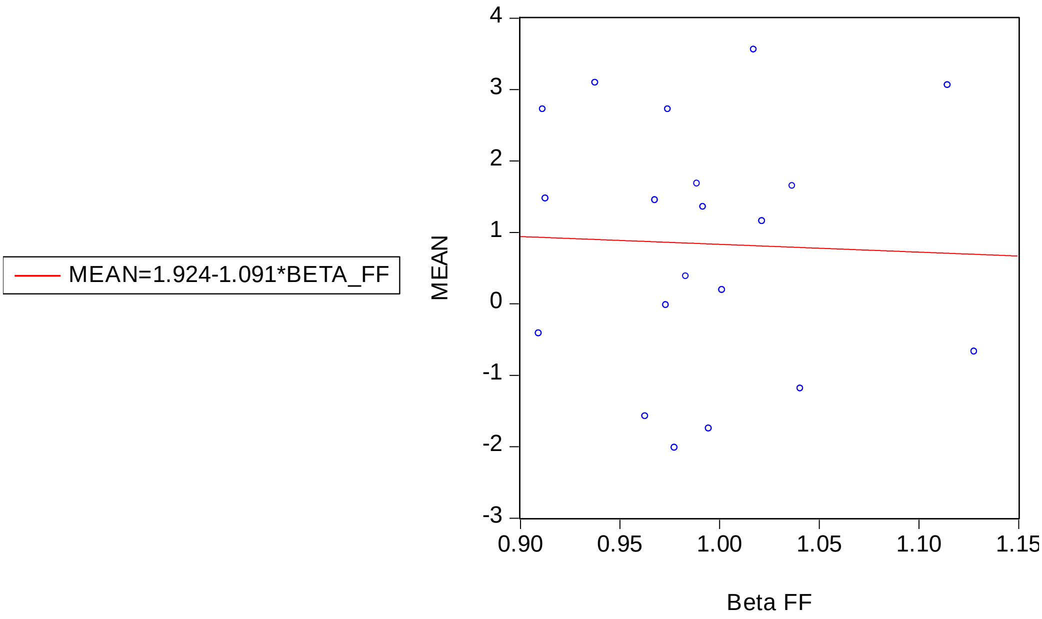
Table 48 - Second Step Regression Beta FF and Mean Returns Indian Portfolios Sub-Periods

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	1.924425	8.636082	0.222835	0.8262
BETA_FF	-1.090877	8.656622	-0.126017	0.9011

R-squared	0.001346	Mean dependent var	0.842023
Adjusted R-squared	-0.054135	S.D. dependent var	1.731646
S.E. of regression	1.777899	Sum squared resid	56.89666
Durbin-Watson stat	2.232713	J-statistic	0.000000
Instrument rank	2		

Figure 35 - Beta FF against Mean Returns Indian Portfolios Sub-Periods without Outliers



To summarize above-mentioned, it is clear that traditional CAPM model proved to explain variation in mean returns for all of the countries when it comes to 6 portfolios testing, with the highest explanatory power in the US. This can be explained by integration and liquidity of the US financial markets opposed to the other markets under consideration. When the number of portfolios has been increased to 25 portfolio, the explanatory power of beta has decreased to 36% for US, 16% for Asia Pacific and zero for India. This confirms our hypothesis that traditional CAPM can be used mainly for advanced economies, but not for emerging markets. However, it is important to note that even within advanced economies the results were quite different for Asia Pacific, thus one should be cautions when relying on CAPM there.

The other test for model specification bias, has confirmed the hypothesis coming from previous literature that traditional CAPM model with only one explanatory variable, has specification bias and thus beta as a measure includes effects of size and value. Once these factors are added into the equation (SMB and HML), we could see that in cases of all three regions the relationship between beta and mean returns became insignificant and flat. This flatness shows that beta does not differentiate between high and low returns, one the size and value effect are removed. Furthermore, the fitted regression lines usually have negative slope, which contradicts the main assumption of the model.

6.3.4 *Downside Risk Measures*

In the previous section, we have looked at the traditional CAPM model testing. This section will adopt the same testing approaches but will examine an alternative model, D-CAPM. The main aim of this section is to compare the results from traditional Sharpe-Lintner CAPM (1964) to D-CAPM suggested by Estrada (2004). To start let's look at US portfolios, one can find calculated mean returns and associated downside betas for each of the portfolios in Table 49.

Table 49 - Downside Beta Results for US Portfolios

Portfolio	**Mean Returns**	**Downside Beta**	**Downside Beta FF**
1	0.92	1.12	1.13
2	0.63	0.97	0.98
3	0.99	1.15	1.11
4	0.69	0.95	0.97
5	1.20	1.23	1.19
6	0.69	1.25	1.2

If we plot the relationship, one can see that it is positive, meaning the higher the downside beta the higher expected returns. However, the points are quite far from the regression line. One can also see that there is on outlier, which is portfolio six (see Figure 36).

Figure 36 - Downside Beta against Mean Return Plot

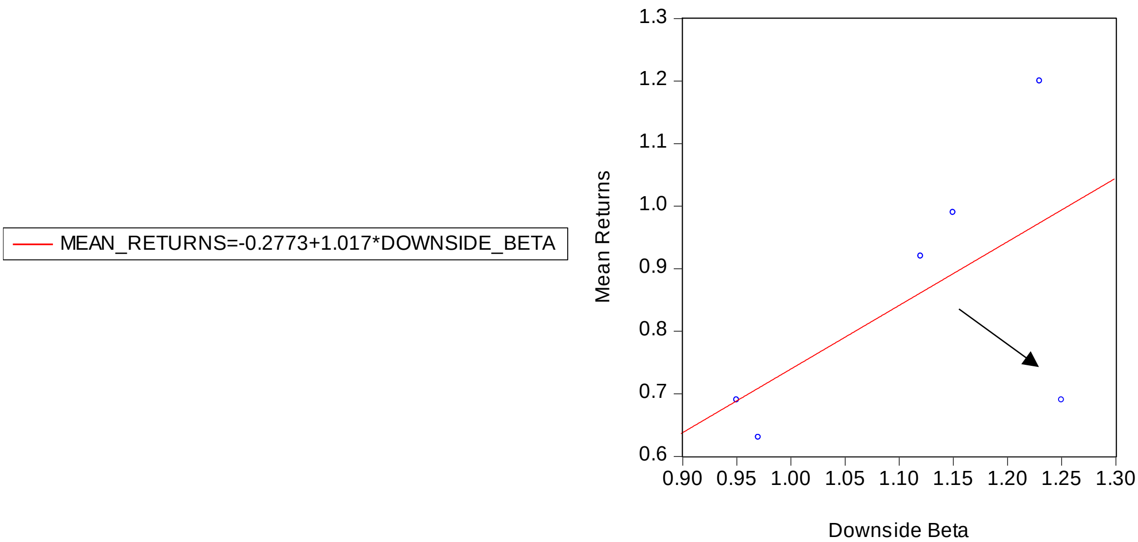


Table 50 - Second-step Regression Downside Beta against Mean Returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.277346	0.545640	-0.508294	0.6380
DOWNSIDE_BETA	1.017103	0.535865	1.898057	0.1305
R-squared	0.339401	Mean dependent var		0.853333
Adjusted R-squared	0.174251	S.D. dependent var		0.222051

S.E. of regression	0.201779	Sum squared resid	0.162860
Durbin-Watson stat	2.403909	J-statistic	0.000000
Instrument rank	2		

As one can see from the results of the regression, γ_1 in front of downside beta is insignificantly positive and the coefficient of determination is as high as 33.9% (see Table 50). However, if we remove observation for portfolio 6 (outlier), one can see that the regression line fits the points more rigorously. Consequently, the regression gives statistically significant results (see Figure 37 and Table 51). In this case, downside beta explains 96% of the variability in mean returns.

Figure 37 - Downside Beta against Mean Return Plot US without Outliers

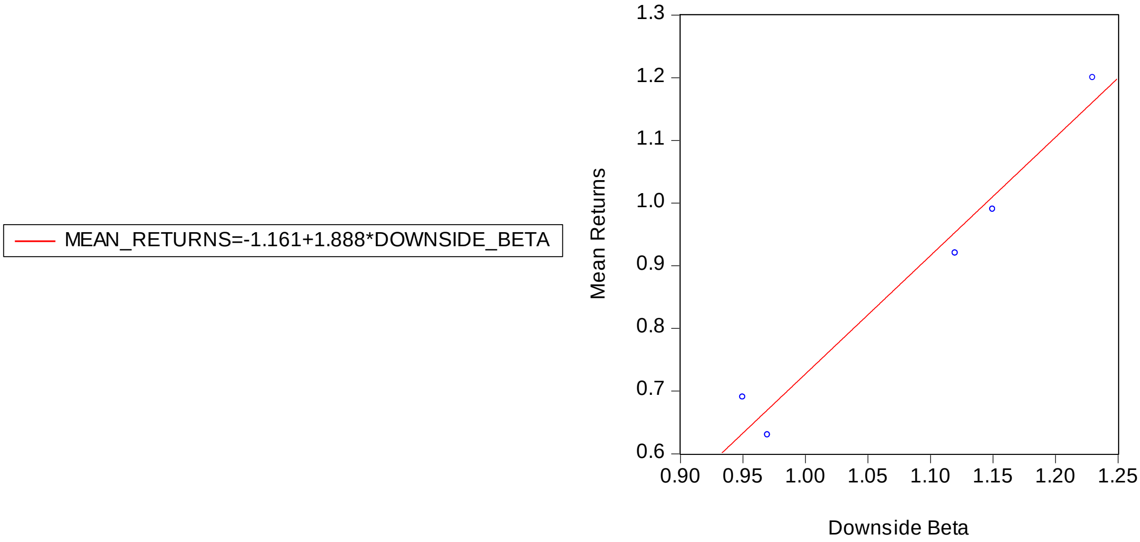


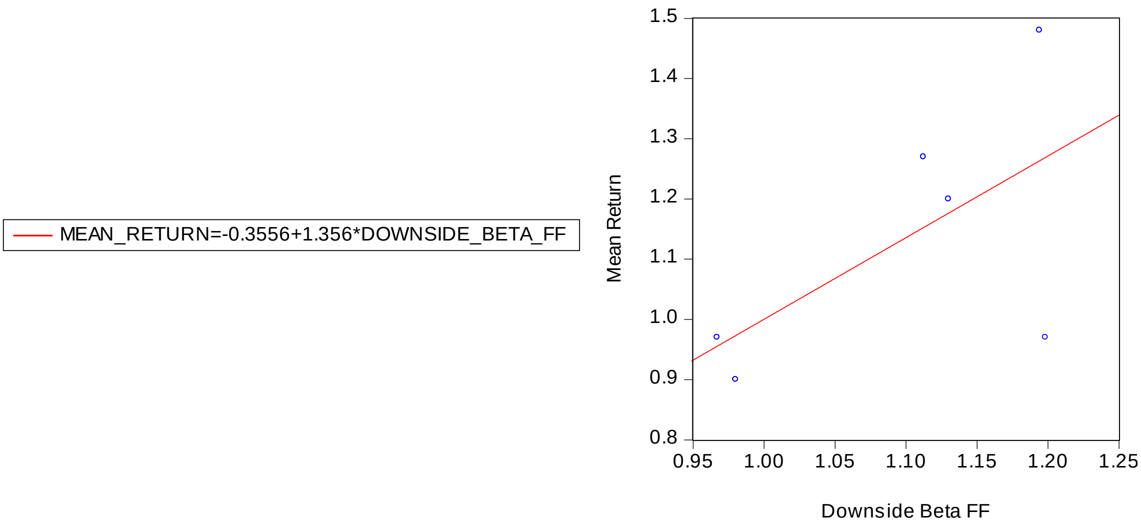
Table 51 - Second-step Regression Downside Beta against Mean Returns US without Outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.161098	0.139985	-8.294473	0.0037
DOWNSIDE_BETA	1.888467	0.117676	16.04797	0.0005

R-squared	0.962896	Mean dependent var	0.886000
Adjusted R-squared	0.950528	S.D. dependent var	0.231582
S.E. of regression	0.051509	Sum squared resid	0.007959
Durbin-Watson stat	0.858966	J-statistic	5.61E-44
Instrument rank	2		

This is the same result as in case of traditional beta. The relationship can be further tested by adding extra factors (size and value) as has been done previously. This test will identify if there was some misspecification in the downside beta. The results for downside beta FF can be seen in the Table 49. If we plot the relationship between downside beta FF and the mean returns, we can see that the regression line fits the point better from the beginning, even though there still is an outlier.

Figure 38 - US 6 Portfolios Downside Beta FF against Mean Returns Plot



Second-step regression also shows that downside beta is significant at 10% explaining up to 37.7% of the variation in the data, with the prediction power of 22.2%. This is a better result than the original second-step regression one can find in Table 50. Thus, we can conclude that adding extra factors helped downside beta to have estimates that are more precise.

Table 52 - Second Step Regression Downside beta FF against Mean Returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.355614	0.595857	-0.596810	0.5828
DOWNSIDE_BETA_FF	1.355817	0.589398	2.300340	0.0829

R-squared	0.377814	Mean dependent var	1.131667
Adjusted R-squared	0.222268	S.D. dependent var	0.224091
S.E. of regression	0.197624	Sum squared resid	0.156220
Durbin-Watson stat	2.322949	J-statistic	0.000000
Instrument rank	2		

Removing outlier (portfolio 6) results in similar results as in previous regression without the extra factors however r-squared has reduced to 93% (Table 53). This shows that downside beta as we have assumed included effects of size and value, however in general they did not affect its explanatory power as much as in case of beta. Thus, when performing estimations these factors should be included into the equation to avoid specification bias.

Table 53 - Second Step Regression Downside beta FF against Mean Returns without Outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.291879	0.143768	-8.985866	0.0029
DOWNSIDE_BETA_FF	2.280927	0.140555	16.22802	0.0005

R-squared	0.930349	Mean dependent var	1.164000
Adjusted R-squared	0.907132	S.D. dependent var	0.234371
S.E. of regression	0.071423	Sum squared resid	0.015304
Durbin-Watson stat	0.487543	J-statistic	3.59E-43
Instrument rank	2		

These results must be taken with caution, as the number of observation is very small. Thus, it makes sense to extend this testing for 25 portfolios, which are available in case of US. The results for the calculation of downside beta and respective mean returns can be found in the Table 54 with graphical plot of the relationship in Figure 39. Similarly, to previous analysis, the data has been checked for outliers and 3 observations were removed based on z-score and Cook's Distance (observations 3, 6 and 24).

Figure 39 - Cook's Distance US 25 Portfolios Downside Beta

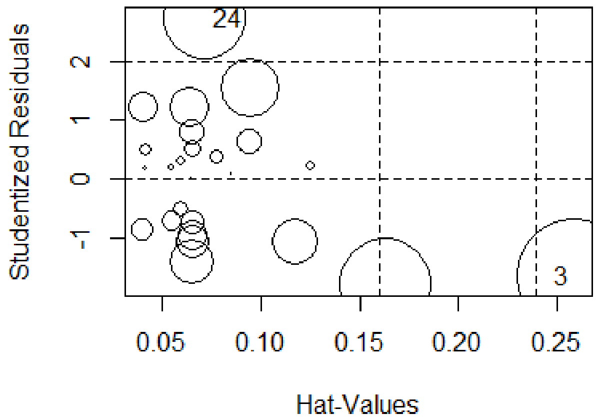
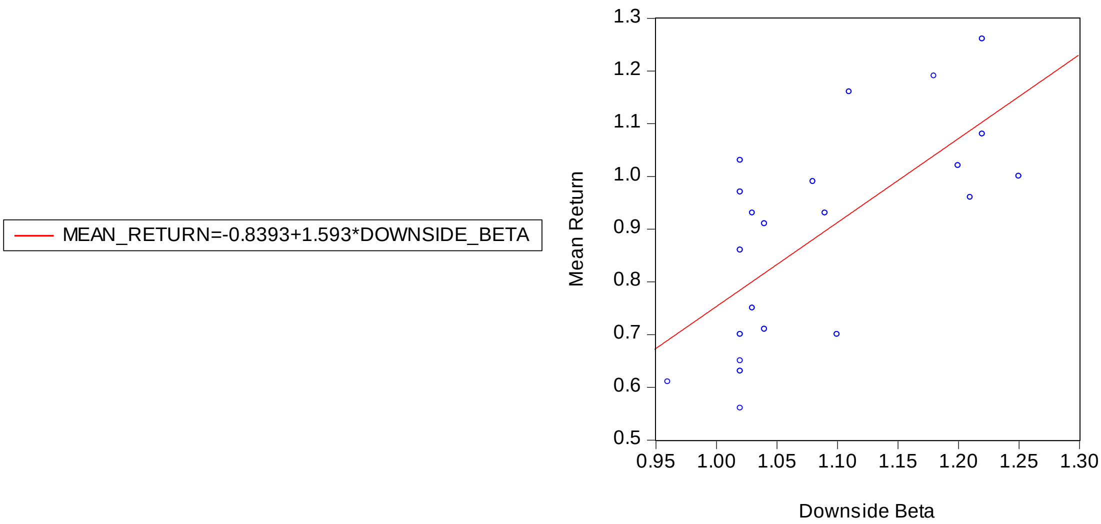


Table 54 - Downside Beta Results for 25 Portfolios US

Portfolios	Mean Return	Downside Beta	Downside Beta FF
1	0.96	1.21	1.23
2	0.61	0.96	0.97
3	0.69	1.34	1.28
4	1	1.25	1.2
5	1.19	1.18	1.14
6	0.62	1.28	1.22
7	0.93	1.09	1.06
8	0.99	1.08	1.05
9	1.08	1.22	1.19
10	1.26	1.22	1.18
11	0.7	1.1	1.07
12	0.91	1.04	1.02
13	0.93	1.03	1.01
14	1.02	1.2	1.18
15	1.16	1.11	1.09
16	0.71	1.04	1.03
17	0.75	1.03	1.02

18	0.86	1.02	1.02
19	0.97	1.02	1.02
20	1.03	1.02	1.01
21	0.63	1.02	1.01
22	0.7	1.02	1.01
23	0.65	1.02	1.02
24	1.37	1.01	1.01
25	0.56	1.02	1.02

Figure 40 - Downside Beta Mean Returns US 25 Portfolios



The second-step regression shows that at this time the model explains 47.2% of the variation in mean returns, which is better result than in case of traditional beta (Table 55). It is also more realistic in comparison to six portfolios, which yielded too optimistic coefficients of determination.

Table 55 - Second Step Regression Downside Beta against Mean Returns US

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.839270	0.338835	-2.476925	0.0223
DOWNSIDE_BETA	1.592633	0.296574	5.370110	0.0000
R-squared	0.472296	Mean dependent var		0.890909
Adjusted R-squared	0.445911	S.D. dependent var		0.200829
S.E. of regression	0.149492	Sum squared resid		0.446956
Durbin-Watson stat	2.096895	J-statistic		0.000000
Instrument rank	2			

When testing for specification bias, the author has recalculated downside beta adding Fama-French factors. Several outliers were identified based on z-score (observation 3, 6 and 1) and thus were removed from the analysis. The results have shown that the predictive power of downside beta has decreased (40.9%) showing that both traditional beta and downside beta included size and value effect. However, opposed to traditional beta, the relationship between downside beta is still significant, which proved superiority of downside beta over traditional beta.

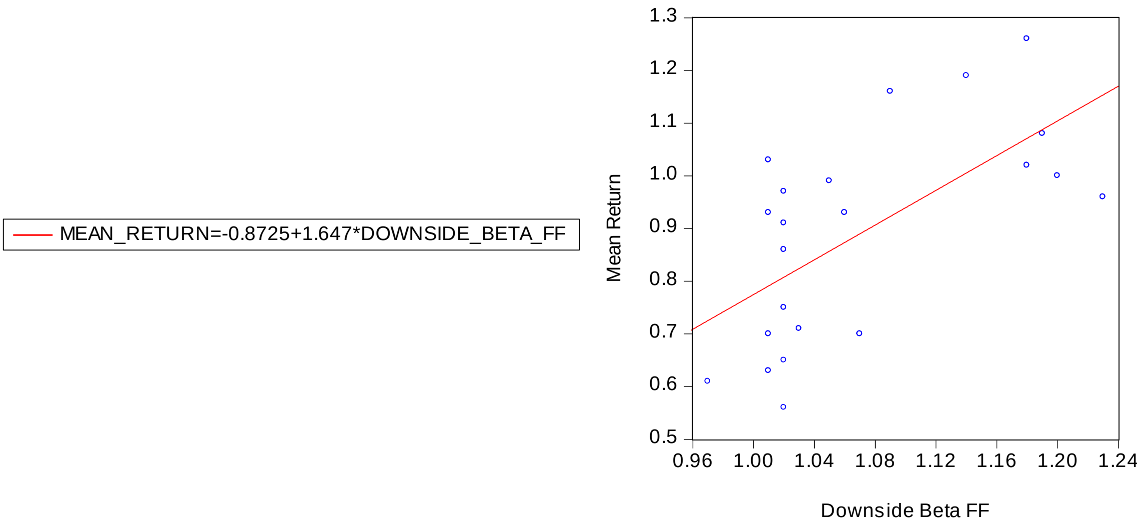
Table 56 - Second Step Regression Downside Beta FF against Mean Returns US 25 Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.872524	0.400691	-2.177547	0.0416
DOWNSIDE_BETA_FF	1.647368	0.365230	4.510497	0.0002

R-squared	0.409791	Mean dependent var	0.890909
Adjusted R-squared	0.380281	S.D. dependent var	0.200829
S.E. of regression	0.158097	Sum squared resid	0.499896
Durbin-Watson stat	1.920571	J-statistic	1.03E-42
Instrument rank	2		

The plot of the relationship also shows that the fitted line is not flat, suggesting that downside beta is capable to discriminate high returns from low returns.

Figure 41 - Downside Beta FF against Mean Returns Plot 25 US Portfolios without Outliers



To confirm these results for DM, it makes sense to look at markets that are less integrated than US market such as Asia Pacific markets represented by 6 and 25 portfolios that we have seen in the previous section. Before we calculate the second-step regression, it is crucial to check the results from the first-step regression for outliers (Table 57 shows results for each portfolio). In case of six portfolios, 6th portfolio was identified as an outlier similarly to the previous analysis and has been removed.

Table 57 - Beta and Beta FF results for 6 Asia Pacific Portfolios

Portfolios	Mean Return	Downside beta	Downside Beta FF
1	1.00	1.05	1.07
2	0.60	0.99	0.98

3	0.57	1.05	1.02
4	0.70	0.96	0.97
5	0.99	1.03	1.02
6	0.10	1.10	1.07

Plotting the relationship, we can see that it is positive; however, the fitted line is quite flat. Based on second-step regression, downside beta relationship with the mean returns is insignificant both at 5% and 10% levels (Table 58).

Figure 42 - Downside Beta against Mean Returns 6 Asia Pacific Portfolios Plot

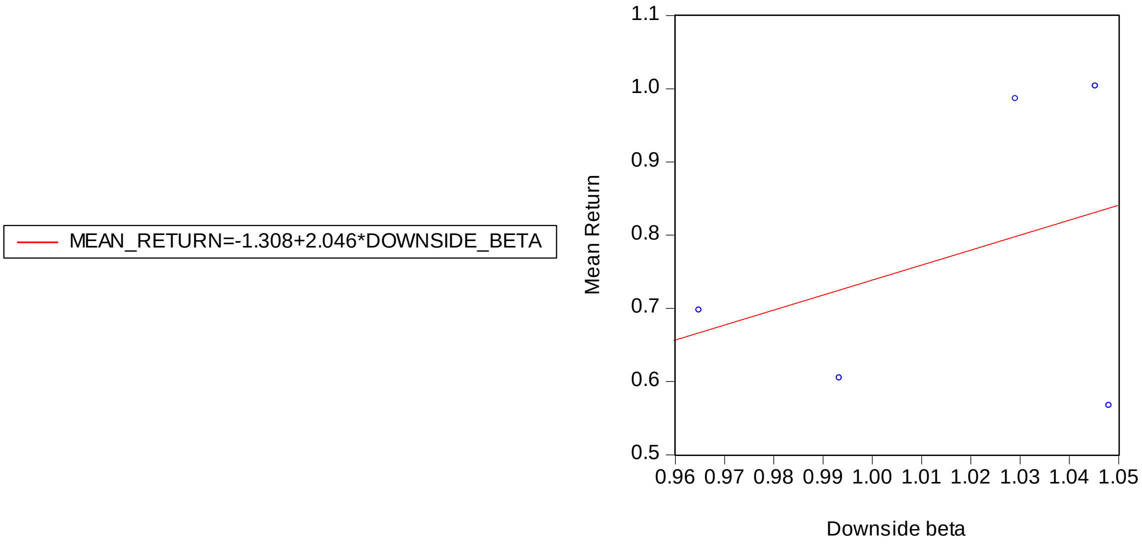


Table 58 - Second Step Regression Downside Beta against Mean Returns without Outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.307600	2.054472	-0.636465	0.5697
DOWNSIDE_BETA	2.046213	2.073633	0.986777	0.3965

R-squared	0.124194	Mean dependent var	0.771656
Adjusted R-squared	-0.167742	S.D. dependent var	0.209142
S.E. of regression	0.226003	Sum squared resid	0.153232
Durbin-Watson stat	1.455312	J-statistic	4.27E-43
Instrument rank	2		

Since the relationship is not significant it is interesting to check if adding extra explanatory variables would somehow alter the relationship. The results for second-step regression (see Table 59) show that when adding extra factors into the regression downside beta becomes significant and explains up to 38.25% of variations in mean returns. When it comes to the prediction power of the model, it is much weaker only around 17.68%. However, these results still outperform traditional beta and therefore one can conclude that downside beta should be preferred. One of the main justification of why traditional beta was not capable to perform well in case of Asia Pacific whereas downside beta turned out to be significant is skewness. Which in case of Asia Pacific and India for majority of portfolios was negative whereas for US positive.

Figure 43 - Asia Pacific 6 Portfolios Downside Beta FF against Mean Returns Plot

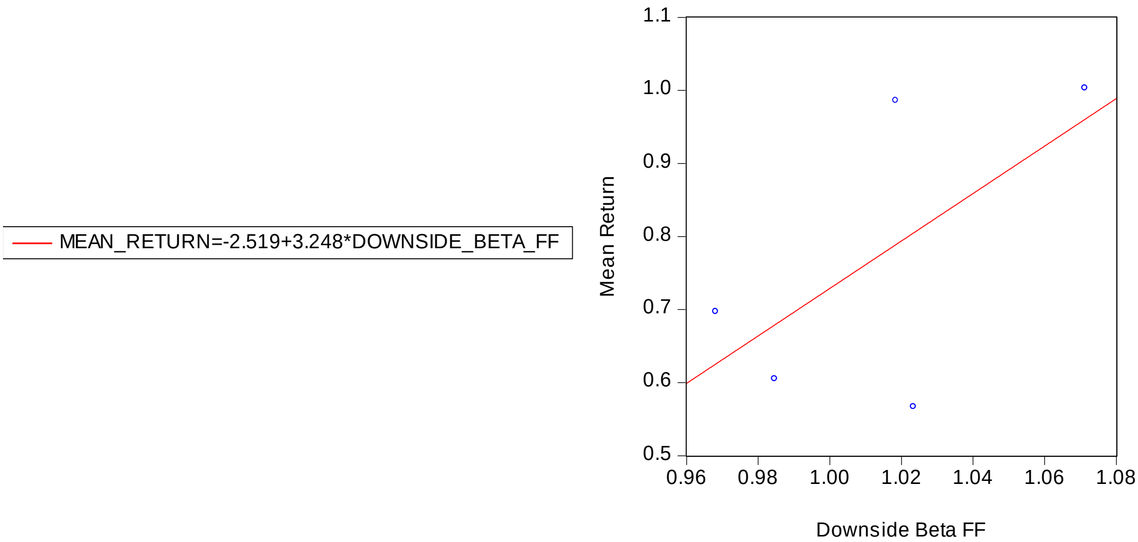


Table 59 - Asia Pacific 6 Portfolios Second Step Regression Downside Beta FF against Mean Returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.519077	1.018414	-2.473530	0.0898
DOWNSIDE_BETA_FF	3.247954	0.997400	3.256420	0.0473
R-squared	0.382577	Mean dependent var		0.771656
Adjusted R-squared	0.176769	S.D. dependent var		0.209142
S.E. of regression	0.189759	Sum squared resid		0.108025
Durbin-Watson stat	1.409366	J-statistic		0.000000
Instrument rank	2			

It is important to check if the relationship between downside beta and mean returns remain the same when the number of observations is increased. One can find results for 25 Asia Pacific Portfolios attached below (Table 60).

Table 60 – Asia Pacific 25 portfolio Results for Downside Beta

Portfolio	Mean Return	Downside Beta	Downside Beta FF
1	1.21	1.09	1.12
2	0.78	1.01	1.00
3	0.60	1.14	1.10
4	0.95	1.07	1.04
5	1.31	1.03	1.00
6	0.15	1.08	1.06
7	0.59	0.97	0.95
8	0.81	0.97	0.96

9	1.13	0.99	0.98
10	0.35	1.08	1.05
11	0.51	1.04	1.02
12	0.96	0.96	0.95
13	0.95	0.91	0.90
14	0.99	1.00	1.01
15	0.78	0.97	0.96
16	1.02	0.89	0.88
17	0.78	0.92	0.92
18	1.03	0.92	0.91
19	1.23	0.91	0.90
20	0.96	0.91	0.90
21	1.04	0.90	0.89
22	0.97	0.90	0.89
23	1.68	0.87	0.87
24	0.71	0.87	0.86
25	0.45	0.90	0.90

For running second-step regression, the author has removed four portfolios due to identifying higher z-score and Cook's Distance (portfolios 4, 6, 10 and 23). If one plots the results, it can be seen that the relationship between downside beta and mean returns is positive. However, several points lie far away from the fitted line meaning the model will have high RSS. Thus, one can assume that the model will not have high explanatory power. To check this, we refer to the results from the second-step regression (Table 61).

Figure 44 - Downside Beta against Mean Returns Plot Asia Pacific

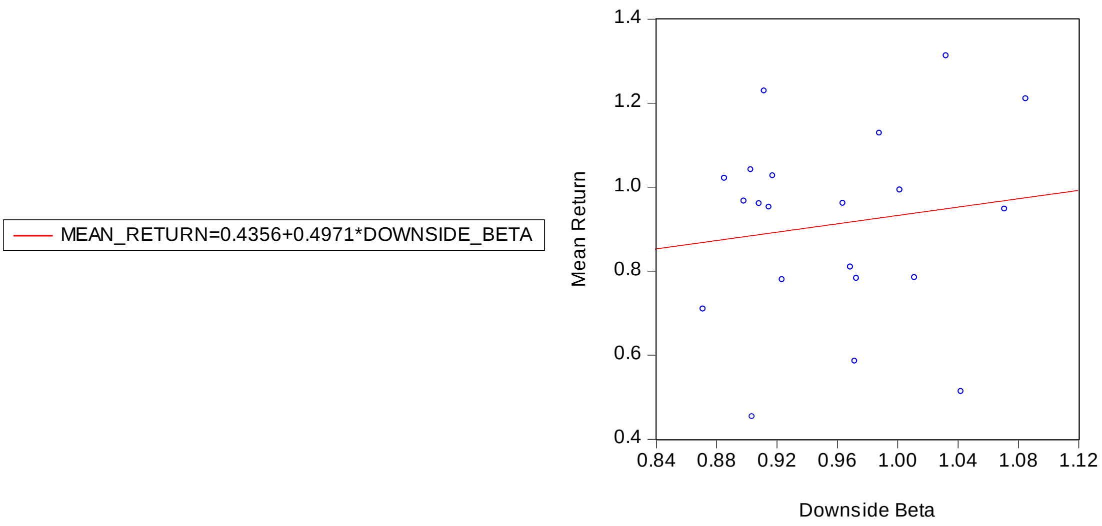


Table 61 - Second Step Regression Downside Beta Asia Pacific

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.306724	0.852279	0.359887	0.7234
DOWNSIDE_BETA	0.628426	0.895339	0.701887	0.4922

R-squared	0.029835	Mean dependent var	0.911148
Adjusted R-squared	-0.027234	S.D. dependent var	0.236435
S.E. of regression	0.239632	Akaike info criterion	0.079880
Sum squared resid	0.976203	Schwarz criterion	0.179294
Log likelihood	1.241143	Hannan-Quinn criter.	0.096705
F-statistic	0.522788	Durbin-Watson stat	2.297555
Prob(F-statistic)	0.479485	Wald F-statistic	0.492645
Prob(Wald F-statistic)	0.492248		

The results, confirm our previous findings. Lambda 1 is insignificant thus showing that downside beta is not significantly different from zero. However, when one would recalculate downside beta with extra factors and remove outliers (observations 1, 23, 6, 3, 11) one can see that the relationship is significant however only at 10% level. The coefficient of determination is also much lower than in case of six portfolios, just 10.8%. Such results can be attributed to portfolios formation technique as the data set is not homogeneous and the results show many outliers for all of the models.

Table 62 - Second Step Regression Downside Beta FF against Mean Returns 25 Asia Pacific Portfolios without Outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.178004	0.647396	-0.274954	0.7867
DOWNSIDE_BETA_FF	1.178473	0.657696	1.791820	0.0910

R-squared	0.108928	Mean dependent var	0.931579
Adjusted R-squared	0.056512	S.D. dependent var	0.219425
S.E. of regression	0.213135	Sum squared resid	0.772250
Durbin-Watson stat	1.189099	J-statistic	4.76E-44
Instrument rank	2		

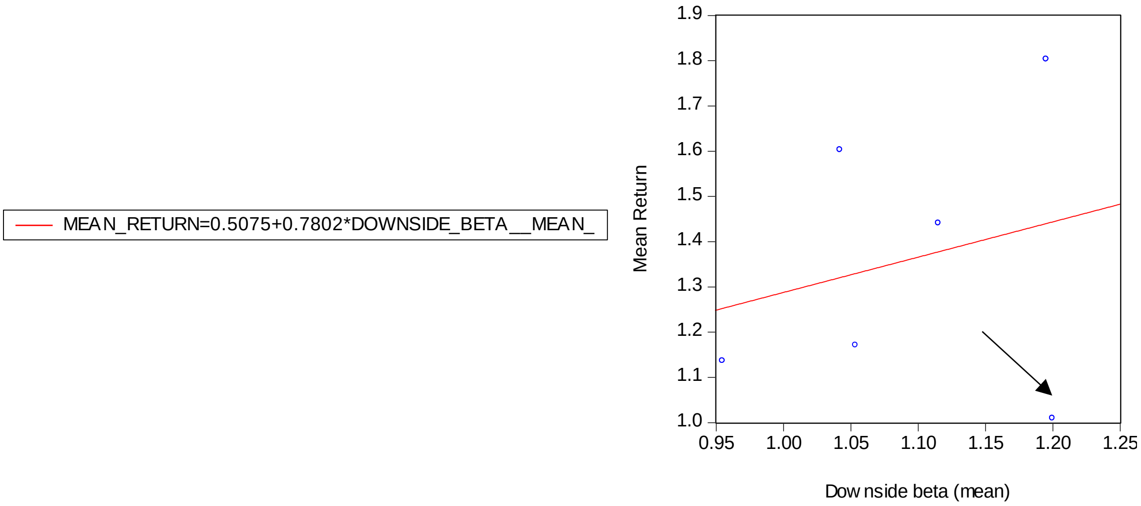
As in the previous section, the second part of testing looks at EM, and focuses on testing of models on six Indian portfolios. The results of downside betas and respected mean returns can be found in the Table 63. The estimated beta coefficients below were calculated with respect to the mean returns.

Table 63 - Downside Risk Measures Indian Portfolios

Portfolios	Mean Excess Return	Downside beta	Downside Beta from FF
1	0.42	1.2	1.33
2	0.55	0.95	0.96
3	0.86	1.12	1.09
4	1.02	1.04	1.14
5	1.22	1.2	1.19
6	0.59	1.05	1.06

If we plot the relationship, we can see that it is positive, however similarly to beta the points are positioned quite far from the regression line. To have a deeper look at the relationship, we run the same second-step regression as before, this time regressing downside beta on mean returns.

Figure 45 - Downside Beta against Mean Returns Indian 6 Portfolios Plot



The results can be found in the Table 64. One can see that downside beta is not significant and coefficient of determination is equal to zero.

Table 64 - Second step regression Downside Beta against Mean Returns Indian Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.691536	1.091298	0.633682	0.5607
DOWNSIDE_BETA_FROM_FF	0.075448	1.072938	0.070319	0.9473
R-squared	0.000945	Mean dependent var		0.776667
Adjusted R-squared	-0.248818	S.D. dependent var		0.308588
S.E. of regression	0.344849	Sum squared resid		0.475683
Durbin-Watson stat	1.182726	J-statistic		0.000000
Instrument rank	2			

However, similarly to previous analysis one can see that there is one outlier in this relationship (portfolio 1). When we remove this observation the relationship between downside beta and mean returns becomes more prominent and significant. According to the results in Table 65, one can see that approximately 62.66% of variations can be explained by downside beta. This is weaker result than in case of traditional better.

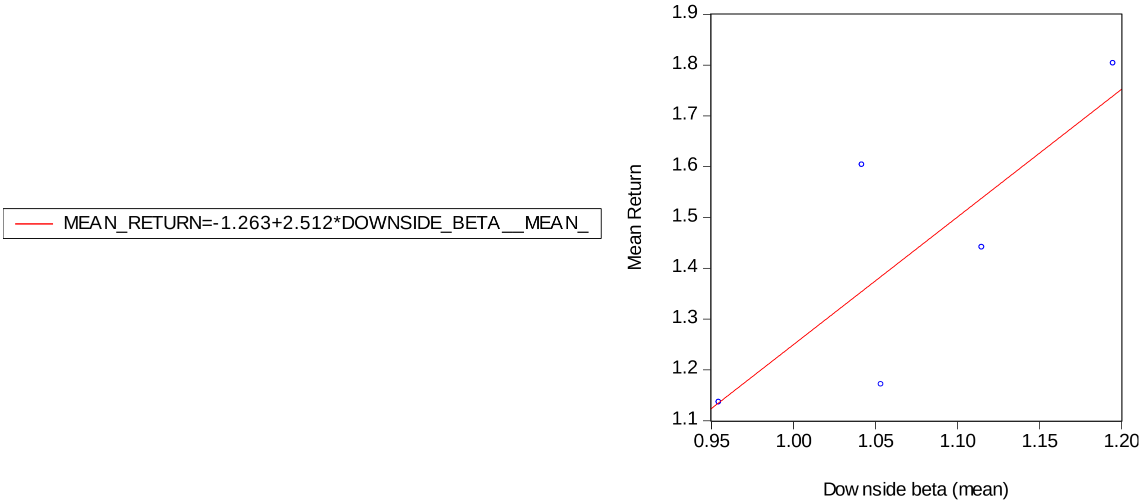
Table 65 - Second step regression Downside Beta against Mean Returns Indian Portfolios without Outliers

White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.262945	0.571477	-2.209966	0.1141
DOWNSIDE_BETA__MEAN_	2.512436	0.492355	5.102896	0.0146
R-squared	0.626697	Mean dependent var		1.430854
Adjusted R-squared	0.502262	S.D. dependent var		0.284019

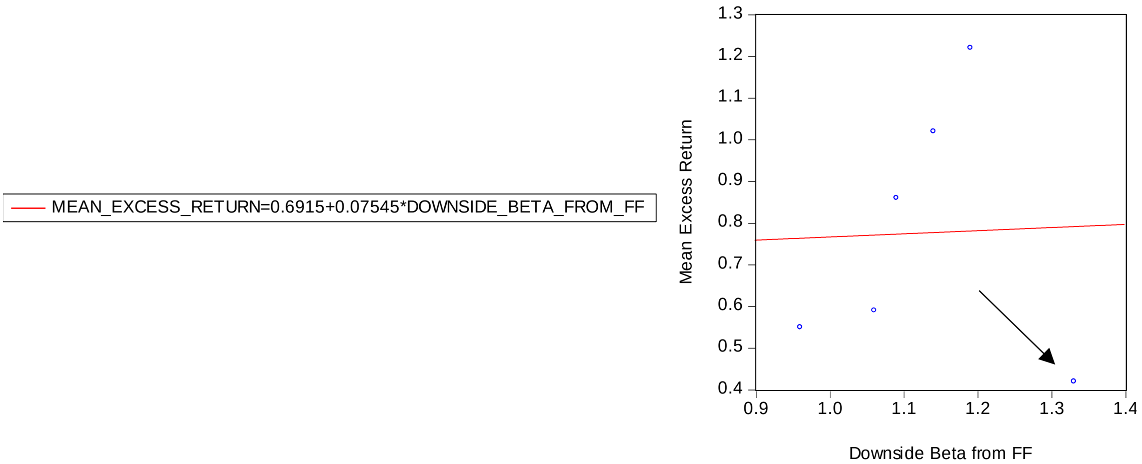
S.E. of regression	0.200377	Akaike info criterion	-0.088057
Sum squared resid	0.120453	Schwarz criterion	-0.244282
Log likelihood	2.220143	Hannan-Quinn criter.	-0.507349
F-statistic	5.036357	Durbin-Watson stat	1.989951
Prob(F-statistic)	0.110532	Wald F-statistic	26.03954
Prob(Wald F-statistic)	0.014555		

Figure 46- Downside Beta against Mean Returns Plot Indian Portfolios



However it make sense to compare beta and downside beta estimations with extra factors included into the regression to check if downside beta stays significant. The results of new downside betas can be seen in Table 63. Opposed to traditional beta downside beta stayed significant. When plotting the relationship, we can see that the points have clear trend and there is one evident outlier. The outlier is still portfolio 1 as in previous case.

Figure 47 - Downside Beta FF and Mean Returns Plot 6 Indian Portfolios



Once this portfolio is removed, we can see that the relationship between downside beta and mean returns is more prominent that in case when extra factors have not been added to the relationship. Therefore, based on the above results one can assume that previous model only with downside beta had a specification bias.

Figure 48 - Downside Beta FF and Mean Returns Plot 6 Indian Portfolios without Outlier

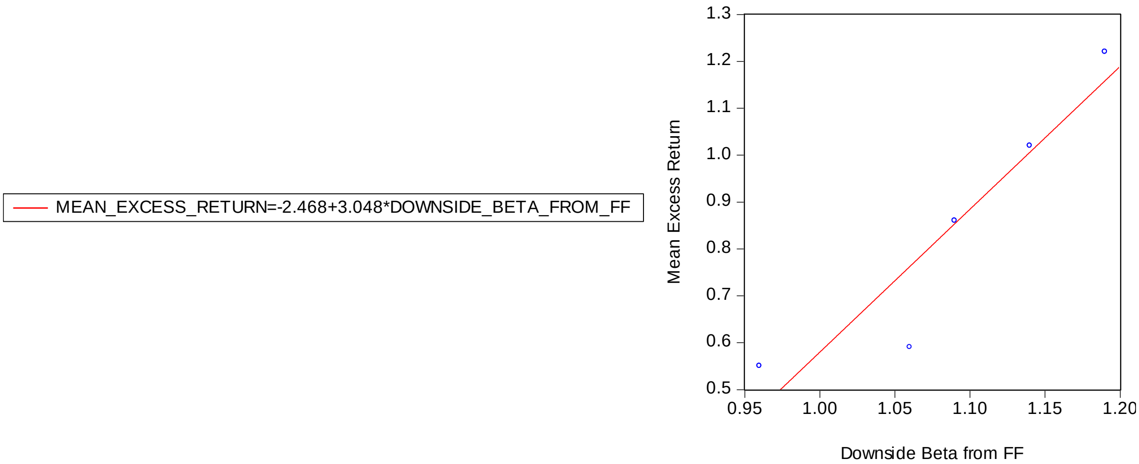


Table 66 - Second Step Regression Downside Beta FF against Mean Returns Indian Portfolios without Outlier

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.467741	0.759492	-3.249198	0.0475
DOWNSIDE_BETA_FROM_FF	3.047556	0.666503	4.572460	0.0196
R-squared	0.869384	Mean dependent var		0.848000
Adjusted R-squared	0.825846	S.D. dependent var		0.284377
S.E. of regression	0.118675	Sum squared resid		0.042252
Durbin-Watson stat	1.524775	J-statistic		1.35E-43
Instrument rank	2			

Based on these results for six Indian portfolios, one can conclude that downside beta should be a prevailing choice as traditional beta is insignificant and its adjusted r-squared is negative, whereas in case of downside beta it is 82.5%.

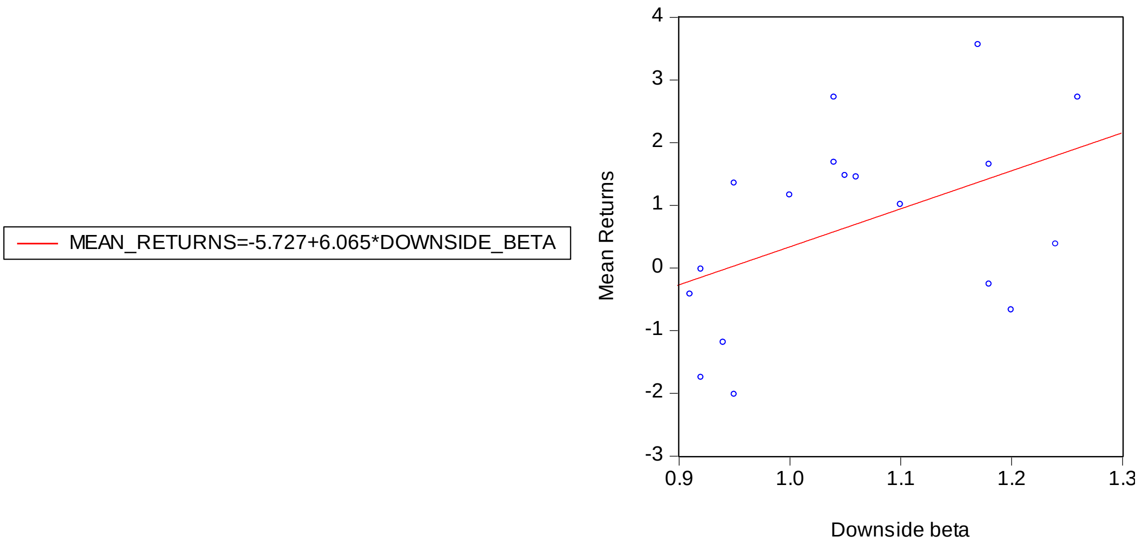
The same way as previously the author decided to estimate sub-period downside betas to increase the number of observations, which in total would yield 23 observation (1 observation removed from portfolio 1 due to missing values). It is important to highlight that five observations were removed from the sample due to z-score higher than 2 (observation 1, 3, 11, 13 and 19).

Table 67 - Downside Beta Sub-periods Indian Portfolios

Observations	Mean Returns	Downside beta	Downside Beta FF
1	-0.71	1.45	1.40
2	1.01	1.10	1.20
3	-1.58	1.59	1.34
4	-0.42	0.91	0.92
5	1.16	1.00	0.99
6	1.35	0.95	0.96
7	-0.02	0.92	0.95

8	-1.75	0.92	0.91
9	2.72	1.04	1.04
10	1.65	1.18	1.14
11	0.47	1.49	1.43
12	-0.67	1.20	1.18
13	3.09	0.89	0.95
14	1.68	1.04	1.04
15	-0.26	1.18	1.11
16	-2.02	0.95	0.91
17	3.56	1.17	1.17
18	2.72	1.26	1.21
19	0.19	1.50	1.37
20	-1.19	0.94	0.93
21	1.47	1.05	1.03
22	1.45	1.06	1.04
23	0.38	1.24	1.22

Figure 49 - Downside Beta against Mean Returns Plot of Sub-periods Results



When plotting sub-period downside betas against the sub-period mean excess returns one can see that the relationship stayed positive as in previous case with just six observations. One can also see that running this regression shows that downside beta is significant at 10%, and explains approximately 21% of the changes in mean returns. Even though, this result is much higher than in case of traditional beta which is not significant at 10% level and has coefficient of determination of zero. Thus, from a given data set one can conclude that on 10% significance level downside beta explains more of the variations in returns than traditional beta. However, the results are inconclusive in regards to 5% significance level and would require more extensive data sets for proper testing.

Table 68 - Second Step Regression Sub-periods of Indian Portfolios

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.726707	3.453021	-1.658463	0.1167
DOWNSIDE_BETA	6.064925	3.321127	1.826165	0.0865

R-squared	0.210875	Mean dependent var	0.712222
Adjusted R-squared	0.161554	S.D. dependent var	1.566805
S.E. of regression	1.434671	Sum squared resid	32.93250
Durbin-Watson stat	2.455139	J-statistic	3.83E-47
Instrument rank	2		

For further examination of downside beta and its strength, the coefficient was re-estimated by adding extra factors as in previous examples. The results can be seen in the Table 67. Removing the same outliers as in previous case gives the relationship that one can see on Figure 50. It is evident that the relationship is positive and the regression line is not flat, meaning that downside beta differentiates between high returns and low returns. The explanatory power of downside beta (approx. 16%) is also higher than in case of traditional beta that lost its significance after additional variables has been introduced. However, one has to be cautious, as the relationship is significant only at 20% level. Even though this results cannot be considered as satisfactory, one can attribute it to the problem of testing methodology and lack of data, as we have seen before the relationship between mean returns and downside beta remained significant after addition of extra factors in case of 6 portfolios. The issue in this case might lie in segregation of periods.

Figure 50 - Downside Beta FF against Mean Returns Plot Indian Portfolios (Sub-Periods) without Outliers

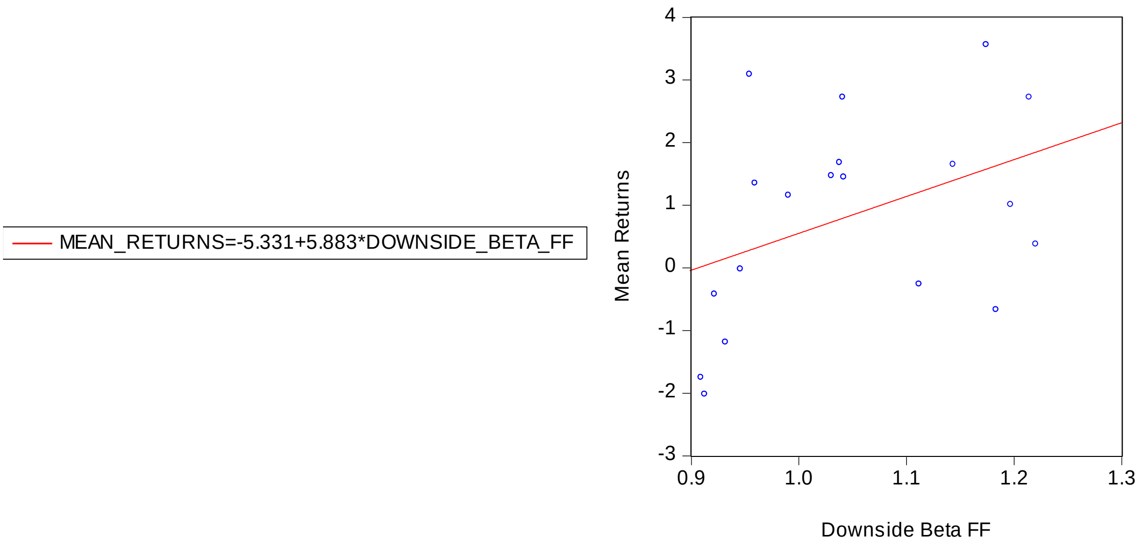


Table 69 - Second Step Regression Downside Beta FF against Mean Returns without Outliers

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.331307	4.303959	-1.238698	0.2323
DOWNSIDE_BETA_FF	5.883497	4.090061	1.438487	0.1685

R-squared	0.165314	Mean dependent var	0.837368
Adjusted R-squared	0.116215	S.D. dependent var	1.617425
S.E. of regression	1.520539	Sum squared resid	39.30467
Durbin-Watson stat	2.535928	J-statistic	0.000000
Instrument rank	2		

To summarise all above-mentioned, one of the key conclusions is that performance of both of the models varies in its strength from market-to-market. It is evident that even within DMs the performance of the traditional CAPM model is the strongest in US and much weaker in other parts. We could also see that downside beta explained more of variation in mean excess returns in DMs opposed to traditional beta and remained significant after inclusion of extra variables with quite high explanatory power of 40.9%. When it comes to emerging markets, in case of Indian portfolios the author would suggest looking at downside beta as a more reliable measure. Despite the fact that its significance for the segregated portfolios proved to be reliable only at 20%, it has still performed much better than traditional beta. These results can be attributed to the data limitations and segregation problem. As a side finding, this research paper has shown unavailability of relevant data (formed portfolios) for emerging markets, which would greatly affect capabilities of practitioners to perform proper testing before using the models.

7 Suggested Area for Future Research

The last objective of this research paper was to provide suggestions for future research in the area of asset pricing in emerging markets and generally. This section is particularly tailored to meet this objective. Traditional unconditional CAPM model and all its above-mentioned modifications rest on one fundamental assumption about investor behaviour, which implies that investors are risk-averse single-period utility maximizers. Despite making estimations quite comfortable, this approach does not account for change in expectations about future returns. This assumption also implies that the riskiness of the firm is constant throughout the time, which greatly contradicts the reality where macroeconomic factors largely influence business profitability (security of cash flows). Furthermore, since the correlation between the firms and the market differ during different stages of business cycle, the beta coefficients should also vary over time (Bali, Engel and Tang 2013, p.2). This was evident from the research results of Time Series Test, where all the beta coefficients were statistically significant but different for each time period.

These arguments lead to a search for a better more realistic alternative, which resulted into introduction of so-called conditional beta models. The most crucial research in this area includes Bollerslev, Engle and Wooldridge (1988); Bolleslav, Engle and Neslon (1994); Braun, Nelson and Sunier (1995); Engle (2002); Andersen, Bollerslev, Diebold and Wu (2006); Bali, Engle and Tang (2013) and Engle (2014). These papers, focused on modelling of time variation in second or higher moments. While previous recognition of time-varying covariances existed (Mandelbrot (1963) and Fama (1965)), it has not been investigated up until early 1980s. When the first ground-breaking research was done by Engle (1982), introducing ARCH models.

The first step towards conditional beta started with implementation of Engle's time-varying covariances into CAPM model. The main claim of this approach was that economic agents have common expectations about future returns, however since they are conditional; these expectations should be regarded as stochastic (Bollerslev, Engle and Wooldridge 1988, p. 117). In their paper, they used multivariate GARCH-in-mean (GARCH-M) model, which implies that conditional mean returns depend on conditional variance of returns (French, Schwert and Staumbaugh, 1987). This model was used to incorporate at least some of the volatility feedback, which is not captured by the basic GARCH. The key finding of Bollerslev, Engle and Wooldridge (1988), was that conditional covariance matrix of the asset returns is strongly autogressive and that it is not constant.

In later research performed by Braun, Nelson and Sunier (1995) it was found that beta exhibits asymmetric response to positive and negative news. This finding confirmed previously supported view that the return volatility tends to rise following good and bad news. To account for this asymmetry they have suggested to apply bivariate ARCH or (EGARCH). The key argument of the empirical finding of the paper, was that there is strong predictive asymmetry both in market and firm volatility, however it was found to be absent in case of conditional betas.

There were a number of other parametric approaches, which suggested alternative methods of estimation time-varying beta based on GARCH models were: VECH and diagonal VECH, constant correlation multivariate GARCH (CC-GARCH) model suggested by Bollerslev (1990) and the BEKK model proposed by Engle and Kroner (1995). These approaches were further tested and several adjustments were suggested by Choudhry (2001, 2005) who used VECH 6 and BEKK models. Faff (2000) proposed estimation of beta with the use of MGARCH, EGARCH and TARCH, whereas Bali (2007) used bivariate GARCH models to estimate time-varying CAPM beta. Other recent approaches in this area include treatment of conditional betas as latent variables such as Ang and Chan (2007) Markov chain Monte Carlo and Gibbs sampling or Adrian and Francozi (2009) Kalman filter.

Another important class of models was introduced by Engle (2002), who suggested new multivariate models – dynamic conditional correlation (DCC), to allow for the flexibility that that was available with the use of univariate GARCH and at the same time allowing for nonlinearity. This new class of multivariate GARCH models can be viewed as generalized constant conditional correlation estimators suggested by Bollerslev (1990). Based on this development Engle, Bali and Tang (2013) have introduced dynamic conditional beta. Their research claims that there is no significant relationship between unconditional beta and that dynamic conditional beta is superior in explanation of daily stock returns.

So far, we have talked about parametric models, which impose certain parametric shape on the development of asset returns and subsequently the volatility. Currently, there is no general agreement on one common kind of structure that can be used for all of the markets. Consequently, this has served as an inspiration for development of non-parametric models such as the one suggested to Andersen, Bollerslev, Diebold, and Wu (2006) or later models such as SURE (Seemingly Unrelated Regression Equations) suggested by Ferreira, Gil-Bazo and Orbe (2008) or quite widely used rolling window approach by Fama and MacBeth (1973). It is quite crucial to highlight that even though conditional parametric and non-parametric frameworks are much more sophisticated, misspecified conditional betas can result in higher pricing errors than static betas Ghysels (1998). Thus, caution should be paid in their estimation and consequent application.

As the result, one can see that the field of asset pricing has evolved and now a new era has emerged that no longer focuses on the importance of unconditional betas, but rather considers time-varying behaviour of volatility. Thus, examination of various GARCH processes to define the best estimator and further comparison of those measures to conditional downside risk measures, should be relevant. One of the possible suggestions would be to look at the GARCH models that allow volatility to exhibit regime-specific behaviour, specifically focusing on two-state Markov switching E-GARCH. Markov switching GARCH models can display properties that reflect the typical characteristics of the financial assets. Opposed to the normal mixture GARCH the conditional probability that volatility is in each regime varies over the time, thus the probability of the market switching from low volatility to high is different than the probability that it will switch from high to low volatility.

8 Conclusions and Recommendations

The aim of this master thesis was to test different risk measures and asset pricing models in the context of emerging markets and compare obtained results to developed markets. The investigation was based on two main approaches to testing. First testing on indices and second testing on portfolios. The first hypothesis related to both testing of indices and portfolios was connected to normality assumption of return distribution. It has been argued, based on previous research, that return distribution would show signs of fat tails, skewness and excess kurtosis. The results show that all the returns (of both indices and portfolios) for advanced and emerging markets exhibit non-normality in their distributions, particularly having fat tails, excess kurtosis and negative skewness. This finding confirms previous research and hypothesis H1 cannot be rejected.

The first part of this research paper then focused on testing of four risk measures (standard deviation, beta, semideviation and downside beta). The two hypotheses related to these sections postulated that downside risk measures would outperform traditional risk measures (H.1.1) and that beta coefficient will have zero association with mean returns (H.1.2). The results for emerging markets were to certain extent supporting these hypotheses. The beta coefficient was found to be insignificant and having an r-squared of zero, which confirmed previous studies of Harvey (1995). It was also found that downside beta was significant and explained roughly 27.39% of variations in mean returns. Thus, hypothesis H.1.1 can be partially accepted from the perspective of superiority of downside beta over traditional beta.

However, strongest association with the mean returns was exhibited by standard deviation (ratio of standard deviation of index "i" to the world index). As the result, one can assume that emerging markets are still segmented and that diversifiable risk still has to be priced. When looking at developed markets, beta coefficient was significant as in case of previous research, however coefficient of determination was equal only to 10%. This time downside beta was the strongest measure of risk with coefficient of determination equalling to 16%. This confirms H.1.1 and rejects H.1.2 for DMs. Thus, based on these findings the author would suggest implementing D-CAPM in developed markets and a ratio of either standard deviation or semideviation in emerging markets (the difference between the two measures is insignificant).

The next section of this research focused on testing for Jensen's alpha assumption (hypothesis H.2.1) which assumed non-zero intercept. The results have partially confirmed previous studies Black, Jensen and Scholes (1972). In the most volatile periods the intercept was statistically significant from zero (mainly positive deviations), meaning that securities earned some unpredicted by beta profits. This was particularly true for risker portfolios (small size and high value). However, no negative intercepts were received. Furthermore, it was evident from the sub-period tests that beta is non-constant. As the result, one of the main assumptions of unconditional beta is violated and conditional models should be preferred.

Lastly, section has focused on testing of CAPM and D-CAPM on different sets of portfolios, namely 6 and 25 US portfolios, 25 Asia Pacific Portfolios and 6 Indian Portfolios. Hypotheses related to this section dealt with weak explanatory power of beta and superiority of downside beta (H.2.2 and H.2.3). The outcomes has shown that traditional beta is statistically significant for all countries except for India, which confirms the main assumption of this paper. Furthermore, once size and value factors were added, it became statistically insignificant. Specification bias was also present in case of downside beta. However, it remained significant after adjusting for size and value effects. Consequently, the author cannot reject hypotheses H.2.2 and H.2.3 and suggests preferring downside beta to traditional beta.

References

Abbas, Q., Ayub, U. and Saeed, S. (2011) 'CAPM- Exclusive Problems Exclusively Dealt', Interdisciplinary Journal of Contemporary Research on Business, 2(12), pp. 947-955.

Abbas, Q., Ayub, U., Sargana, S. and Saeed, S. (2011) 'From Regular-beta CAPM to Downside-beta CAPM', *European Journal of Social Sciences*, 21(2), pp. 189-201.

Affleck-Graves, J. and McDonald (1989) 'Nonnormalities and Tests of Asset Pricing Theories', *The Journal of Finance*, 44(4), pp. 889-908.

Agarwalla, S. K., Jacob, J. and Varma, J. R. (2013) 'Fama French and Momentum Factors: Data Library for Indian Market', Indian Institute of Management, Available at: http://www.iimahd.ernet.in/~iffm/Indian-Fama-French-Momentum/four-factors-India-90s-onwards-IIM-WP-Version.pdf (Accessed at: 29th of April 2017).

Agarwalla, S., Jacob, J. and Varma, J. (2013) '*Four Factor model in Indian equities market*', W.P. No. 2013-09-05. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2334482 (Accessed at: 29th of April 2017).

Anderson, T., Bollerslev, T., Diebold, F. and Wu, G. (2006) 'Realized Beta: Persistence and Predictability', Advances in Econometrics, 20, pp. 1-39.

Ang, A., and Chen, J. (2005) CAPM over the Long Run: pp.1926-2001.

Ang, A., Chen, J. and Xing, Y. (2006) 'Downside Risk', Review of Financial Studies, 19(4), pp. 1191-1239.

Ang, and Chua (1979) 'Composite measures for the evaluation of investment performance', Journal of Financial and Quantitative Analysis, 14 (1979), pp. 361-384.

Aparacio, F. and Estrada, J. (1997) 'Empirical distributions of stock returns: European securities markets, 1990± 95', Department of Statistics and Econometrics and Department of Business Economics, Universidad Carlos III de Madrid, Working Paper No. 97± 23.

Aparicio, F. and Estrada, J. (1997) 'Empirical Distribution of Stock Returns: European Security Markets' European Jounral of Finance,

Bali, T. (2007) 'The intertemporal relation between expected returns and risk', Journal of Financial Economics, 87(2008), pp. 101-131.

Bali, T., Engle, R. and Tang, Y. (2013) 'Dynamic Conditional Beta is Alive and Well in the Cross-section of Daily Stock Returns', Georgetown McDonough School of Business Research Paper.

Bali, T.G. (2008) 'The intertemporal relation between expected returns and risk', Journal of Financial Economics, 87, pp. 101-131.

Banz, R. W., (1981) 'The relationship between return and market value of common stock', Journal of Financial Economics, March, pp. 3-18.

Bawa, V. and E. Lindenberg (1977) 'Capital market equilibrium in a mean-lower partial moment framework', Journal of Financial Economics, 5, pp. 189-200.

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

Beaulieu, M.-C., Dufour, J.-M. and Khalaf, L. (2005) 'Exact multivariate tests of asset pricing models with stable asymmetric distributions', in M. Breton and H. Ben Ameur, eds, 'Numerical Methods in Finance', The Netherlands: Kluwer.

Black, F. (1972) 'Capital market equilibrium with restricted borrowing', *The Journal of Business,* 45 (3), pp. 444-455.

Black, F., (1993) 'Estimating Expected Return', *Financial Analysts Journal 49,* pp. 36–38.

Black, F., Jensen, and Scholes, M. (1972) 'The capital asset pricing model: Some empirical tests', *Studies in the theory of capital markets,* pp. 79-121. Praeger: New York.

Blume, M., and I. Friend, (1973) 'A New Look at the Capital Asset Pricing Model', Journal of Finance, 28, pp. 19–33.

Bollerslev, T. (1990) 'Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH approach', *Review of Economics and Statistics 72,* pp. 498–505.

Bollerslev, T., Chou, R. and Kroner, K. (1992) 'ARCH modelling in finance', Journal of Econometrics, 52 (1992), pp. 5-59.

Bollerslev, T., Engle, R. and Wooldrige, J. (1988) 'A capital asset pricing model with timevarying covariances', *Journal of Political Economy,* 96, pp. 116-131.

Bonomo, M. and Garcia, R. (2001) 'Tests of conditional asset pricing models in the Brazilian stock market', *Journal of International Money and Finance,* 20(2001), pp. 71-90.

Braun, F., Nelson, D. and Sunier, A. (1995) 'Good News, Bad News, Volatility, and Betas', *The Journal of Finance,* 50(5), pp. 1575–1603.

BRICS (2017) *Economic Data and Trade Statistics.* Available at: http://brics.itamaraty.gov.br/ (Accessed at: 29th of April 2017).

Campbell, J.Y., and Hentschel, L., (1992) 'No news is good news: An asymmetric model of changing volatility in stock returns', *Journal of Financial Economics,* 31, pp. 281-318.

Chan K. and Chen N. (1988) 'An unconditional asset pricing test and the role of firm size as an instrumental variable for risk', *The Journal of Finance,* 43:309-325.

Cochrane, J. (2005) “*Asset Pricing*”, 2nd edn. United States: Princeton University Press.

Davis, J., Eugene, F., & Kenneth, F. (2000) ‘Characteristics, co variances and average returns: 1929 to 1997’, *The Journal of Finance,* 55 (1), pp. 389-406.

Dzaja, J. and Aljinovic, Z. (2013) ‘Testing CAPM Model on the Emerging Markets of the Central and Southeastern Europe’, *Croatian Operational Research,* Vol. 4. pp. 164-175.

Engle, R. (2002) ‘Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models’, *Journal of Business and Economic Statistics 20,* pp. 339–350.

Engle, R.F., (1982) ‘Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation’, *Econometrica 50*, pp. 987–1007.

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

Estrada, J. and Serra, A. (2005) ‘Risk and return in emerging markets: Family matters’, *Journal of Multinational Financial Management*, 15, pp. 257-272.

Fabozzi, F. and J. Francis (1978) ‘Beta as a random coefficient’, *Journal of Financial and Quantitative Analysis*, 13, pp. 101-116.

Fabozzi, Frank J., Sergio M. Focardi, and Petter N. Kolm. (2010) “Quantitative equity investing: Techniques and strategies.” United States: John Wiley & Sons.

Faff, R. W., Hillier, D. and Hillier, J. (2000) ‘Time varying beta risk: an analysis of alternative modeling techniques’, *Journal of Business Finance and Accounting*, 27, pp. 523-554.

Fama, E., & French, K. (1992) ‘The cross section of expected return’, *The Journal of Finance*, 47 (2), pp. 427-465.

Fama, E., & French, K. (1996) ‘Multifactor explanation of asset pricing anomalies’, *The Journal of Finance,* 51(1), pp. 55-87.

Fama, E., & French, K. (2004) ‘The capital asset pricing model: theory and evidence’, *Journal of Economic Perspectives,* 18 (3), 607-636.

Fama, E., & MacBeth, J. (1973) ‘Risk, return and equilibrium: empirical tests’, *Journal of Political Economy,* 81(3), pp. 607-636.

Fama, E., and French, K. (1993) ‘Common risk factors in the returns on stocks and bonds’, *Journal of Financial Economics*, 33 (1), pp. 3-56.

Ferreira, E., Gil-Bazo, J. and Orbe, S. (2008) ‘Nonparametric Estimation of Conditional Beta Pricing’, *Business Economic Series 03*. [Online]. Available at:http://e-archivo.uc3m.es/bitstream/handle/10016/2612/wb082403.pdf?sequence=1 (Accessed at: 29th of April 2017).

Fishburn, P. (1977) ‘Mean-Risk Analysis with Risk Associated with Below-Target Returns’, *American Economic Review,* 67(2), pp. 116-126.

Franses, P. and Hafner (2003) ‘A Generalized Dynamic Conditional Correlation Model for Many Asset Returns’, *Econometric Institute Report EI 2003-18.*

French, K. (2017) *Data Library*. Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (Accessed at: 29th of April 2017).

French, K. Schwert, W. and Staumbaugh, R. (1987) ‘Expected Stock Returns and Volatility’, *Journal of Financial Economics,* 19 (1987), pp. 3-29.

Galagedera, D, and Jaapar, A. (2008) ‘Modelling time-varying downside risk’, *The Icfai University Journal of Financial Economics*, 7(1), pp.

Galagedera, D. and Brooks, R. (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, pp. 214-230.

Ghysels, E. (1998) ‘On Stable Factor Structures in the Pricing of Risk: Do Time-Varying Betas Help or Hurt? ’, *The Journal of Finance*, 53(2), pp. 549–573.

Gul, F. (1991) ‘The Theory of Disappointment Aversion’, Econometrica, 59(3), pp. 667-686.

Hansen, L. (1982) ‘Large sample properties of generalized method of moment’s estimators’, *Econometrica 50*, pp. 1029-1054.

Hansen, L. and Jagannathan, R. (1997) ‘Assessing specification errors in stochastic discount factor models’, *Journal of Finance 62*, pp. 557-590.

Harlow, W. and Rao, R. (1989) ‘Asset Pricing in Generalized Mean-Lower Partial Moment Framework: Theory and Evidence’, Journal of Financial and Quantitative Analysis, 24(3), pp. 288-311.

Harvey, C. (1995) ‘Predictable risk and returns in emerging markets’, Review of Financial Studies, 8 (3), pp. 773-816.

Harvey, C. and Siddique, A. (2000) ‘Conditional Skewness in Asset Pricing Tests’, The Journal of Finance, 5(3), pp. 1263-1296.

Hogan, W. and J. Warren (1974) ‘Toward the development of an equilibrium capital-market model based on semivariance’, Journal of Financial and Quantitative Analysis, 9, pp. 1–11.

IMF (2016) *Understand the Slowdown of Capital Flows into Emerging Markets*, Chapter 2. Available at: https://www.imf.org/en/News/Articles/2015/09/28/04/53/sores040616b (29th of April 2017).

IMF (2017) The Drivers of Capital Flows in Emerging Markets Post Global Financial Crisis. *Source: IMF Website*.

Iqbal, J and R. Brooks (2007) ‘Alternative beta risk estimators and asset pricing tests in emerging markets: The case of Pakistan’, Journal of Multinational Financial Management, 17, pp. 75-93.

Iqbal, J. and Brooks, R. (2007) ‘A Test of CAPM on the Karachi Stock Exchange’, International Journal of Business, 12(4), pp. 431-443.

Iqbal, J., Brooks, R. and Galagedera, D. (2010) ‘Testing conditional asset pricing models: An emerging market perspective’, *Journal of International Money and Finance*, 29(5), pp. 897–918.

Jagadeesh, N., (1992) ‘Does market risk really explain the size effects?’ *Journal of Financial and Quantitative Analysis 27*, pp. 337-351.

Jagannathan, R., Skoulakis, G. and Wang, Z. (2002) ‘The Analysis of the Cross Section of Security Returns’, *Handbook of Financial Econometrics*. Volume 1, 1st Edition. pp. 73-134.

Kahneman, D. and Tversky, A. (1979) ‘Prospect Theory: An Analysis of Decision under Risk’, Econometrica, 47(2), pp. 263-291.

Khan, M., Gul, M., Khan, N., Nawaz, B., & Sanaullah. (2012) ‘Assessing and testing the capital asset pricing model (CAPM): a study involving KSE-pakistan’, *Global Journal of Management and Business Research*, 12 (10), 32-38.

Lettau, M. and Ludvigson, S. (2001) ‘Consumption, Aggregate Wealth, and Expected Stock Returns’, The Journal of Finance, 6(3), pp. 815-845.

Levy, H. (1978) ‘Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio’, American Economic Review, Sept., pp. 643-4558.

Levy, H. and Markowitz, H.M. (1979) ‘Approximating Expected Utility by a Function of Mean and Variance’, *American Economic Review,* 69(3), pp. 308-17.

Lintner, J. (1965a) ‘The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets’, *Review of Economics and Statistics*, 47 (1), pp. 13-37.

Lintner, J. (1965b) ‘Security Prices, Risk and Maximal Gains from Diversification’, *The Journal of Finance,* 20 (4), pp. 587–615.

Lintner, J. (1969) ‘The Aggregation of Investors Diverse Judgments and Preferences in Purely Competitive Security Markets’, *Journal of Financial and Quantitative Analysis,* 4 (4), pp. 347–400.

Long, J. (1972) ‘Wealth, Welfare and the Price of Risk’, The Journal of Finance, 27(2), pp. 419–433.

MacKinlay, A. (1987) ‘On multivariate tests of the CAPM’, *Journal of Financial Economics*, 18, pp. 341-372.

MacKinlay, A. and Richardson, M. (1991) ‘Using generalized method of moments to test mean-variance efficiency’, *Journal of Finance 46*, pp. 551-527.

Mao, J. (1970) ‘Essentials of Portfolio Diversification’, The Journal of Finance. 25(5), pp. 1109–1121.

Mandelbrot, B. (1963) ‘The Variation of Certain Speculative Prices’, *The Journal of Business*, 36(1963), pp. 394-419.

Markowitz, H. (1991) ‘Foundations of Portfolio Theory’, *The Journal of Finance*. 46(2), pp. 469-477.

McKenzie, M.D., Brooks, R.D., Faff, R.W. and Y.K. Ho (2000) ‘Exploring the economic rationale of extremes in GARCH generated betas: The case of. US banks’, *The Quarterly Review of Economics and Finance*, 40, pp. 85-106.

Merton, R. (1973) ‘An intertermporal capital asset pricing model’, *Econometrica*, 41 (5), pp. 867-887.

Miller, M. H. and Scholes, M. (1972) "Rates of Return in Relation to Risk: A Re-examination of Some Recent Findings," in ed. Michael C. Jensen, Studies in the Theory of Capital Markets. New York: Praeger.

Mossin, J. (1966) ‘Equilibrium in a Capital Asset Market’, *Econometrica 34*, p. 768.

Mossin, J. (1966) ‘Equilibrium in a Capital Asset Market’, Econometrica, 34(4), pp. 768-783.

Munk, C. (2013) “*Financial Asset Pricing Theory*”, 1st edn. United Kingdom: Oxford University Press.

Nawrocki, D. (1999) ‘A Brief History of Downside Risk Measures’, Journal of Investing, 8(3) pp. 9-26.

Newey, W., and West, K. (1987) ‘Hypothesis testing with efficient method of moments estimation’, *International Economic Review 28*, pp. 777-787.

Nielsen, O. E., Kinnebrock, S. and Shephard, N. (2010) ‘Measuring downside risk – realised semivariance, in Volatility and Time Series Econometrics’, Essays in Honour of Robert F. Engle, ed. by T. Bollerslev, J. Russell, and M.Watson. UK: Oxford University Press.

Nieto, B. Orbe, S. and Zarraga, A. (2014) ‘*Time-Varying market beta: does the estimation methodology matter*?’, SORT-Statistics and Operations Research Transactions. Available at:http://www.raco.cat/index.php/SORT/article/view/277216 (Accessed at: 29th of April 2017).

Nimal, P., & Fernando, S. (2010) ‘The conditional relation between beta and returns: evidence from japan and sri-lanka’, Proceedings of International Research Conference on Management & Finance 2010, 1, pp. 178-188.

Orbe, S., Ferrerira, E. and Gil-Bazo, J. (2008) Nonparametric Estimation of Conditional Beta Pricing Models. Working Paper 08-24, *Business Economic Series 03*. Spain: Universidad Carlos III de Madrid.

Pettengill, G., Sundaram, S. and Mathur, I. (1995) ‘The Conditional Relation between Beta and Returns’, *Journal of Financial and Quantitative Analysis*, JSTOR [Online]. Available at:https://www.jstor.org/stable/2331255?seq=1#page_scan_tab_contents (Accessed at: 29th of April 2017).

Reinganum, M. (1981) ‘Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values’, Journal of Financial Economics 9, March, pp.19-46.

Richardson and Smith (1993) ‘A Test for Multivariate Normality in Stock Returns’, The Journal of Business, 66(2), pp. 295-321.

Roll, R. (1977) ‘A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory’, Journal of Financial Economics, 4(2), pp. 129-176.

Ross, S. (1976) ‘The arbitrage theory of capital asset pricing’, *Journal of Economic Theory 13*, pp. 341-360.

Ross, S. (1977) ‘The determination of financial structure: the incentive-signalling approach’, The Bell Journal of Economics, 8(1), pp. 23-40.

Roy, A (1952) ‘Safety-First and the Holdings of Assets’, *Econometrica 20*, pp. 431-449.

Rozeff, M. and Kinney, W. (1976) ‘Capital market seasonality: The case of stock returns’, Journal of Financial Economics, 3(4), pp. 379-402.

Schiffler, R. (1988) ‘Maximum Z Score and Outliers’, *The American Statistician*, 42(1), pp. 79-80.

Shah, N., Dars, J. and Harron, M. (2015) ‘Asset Pricing Model Conditional on Up and Down Market for Emerging Market: The Case of Pakistan’, *European Journal of Business and Management*, 7(1), pp. 15-27.

Sharpe, W. F. (1964) ‘Capital asset prices: a theory of market equilibrium under conditions of risk’, *Journal of Finance*, 19 (3), pp. 425-442.

Stattman D. (1980) ‘Book values and stock returns’, The Chicago MBA: A Journal of Selected Papers, 4:25-45.

Tahir, Abbas, Sargana, Ayub and Saeed (2013) ‘An Investigation of Beta and Downside Beta Based CAPM – Case Study of Karachi Stock Exchange’, *American Journal of Scientific Research*. pp. 118-135.

Tobin, J. (1958) ‘Liquidity Preference as Behaviour towards Risk’, *The Review of Economic Studies*, 25(1), pp. 65-86.

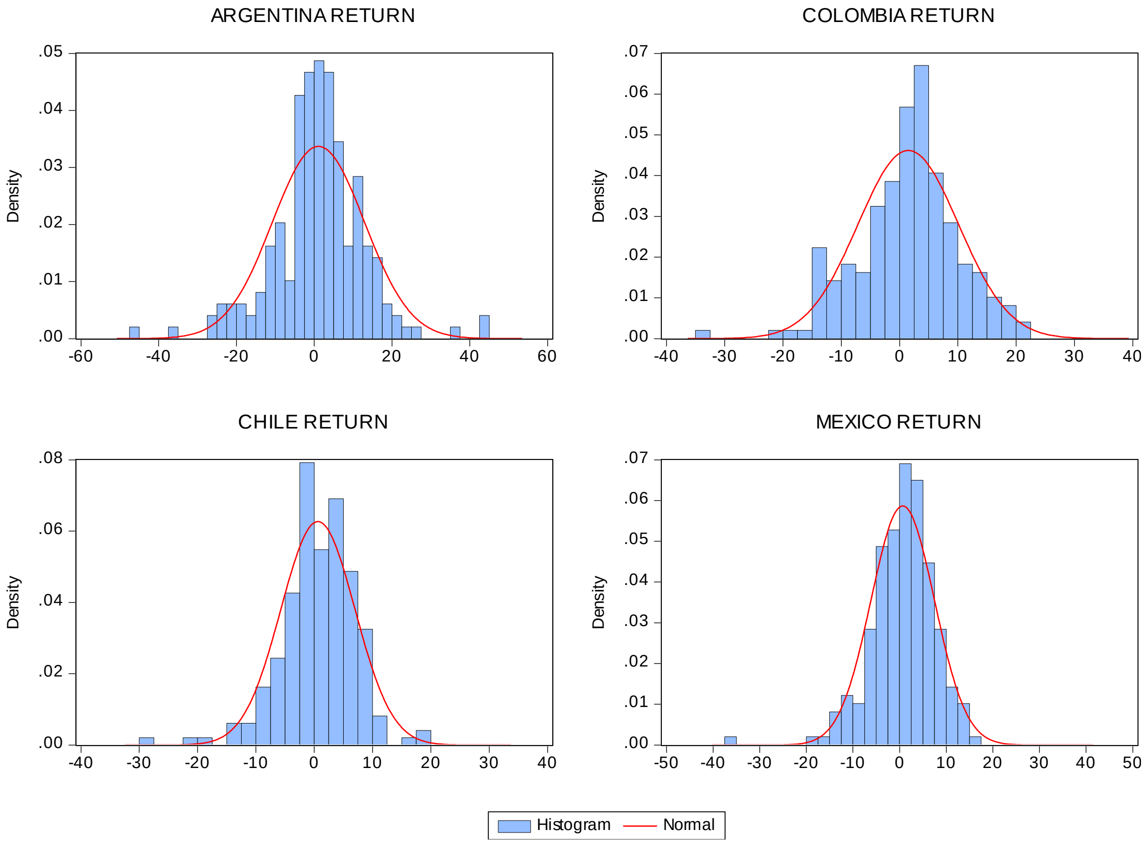
Treynor, J., (1961) ‘Market Value, Time, and Risk’. Available at SSRN: https://ssrn.com/abstract=2600356 or http://dx.doi.org/10.2139/ssrn.2600356 (Accessed at: 9th May 2017).

Zhang, J., and Wihlborg, C. (2010) ‘CAPM in Up and Down Markets: Evidence from Six European Emerging Markets’, *Journal of Emerging Market Finance*, 9 (2), pp. 229-255.

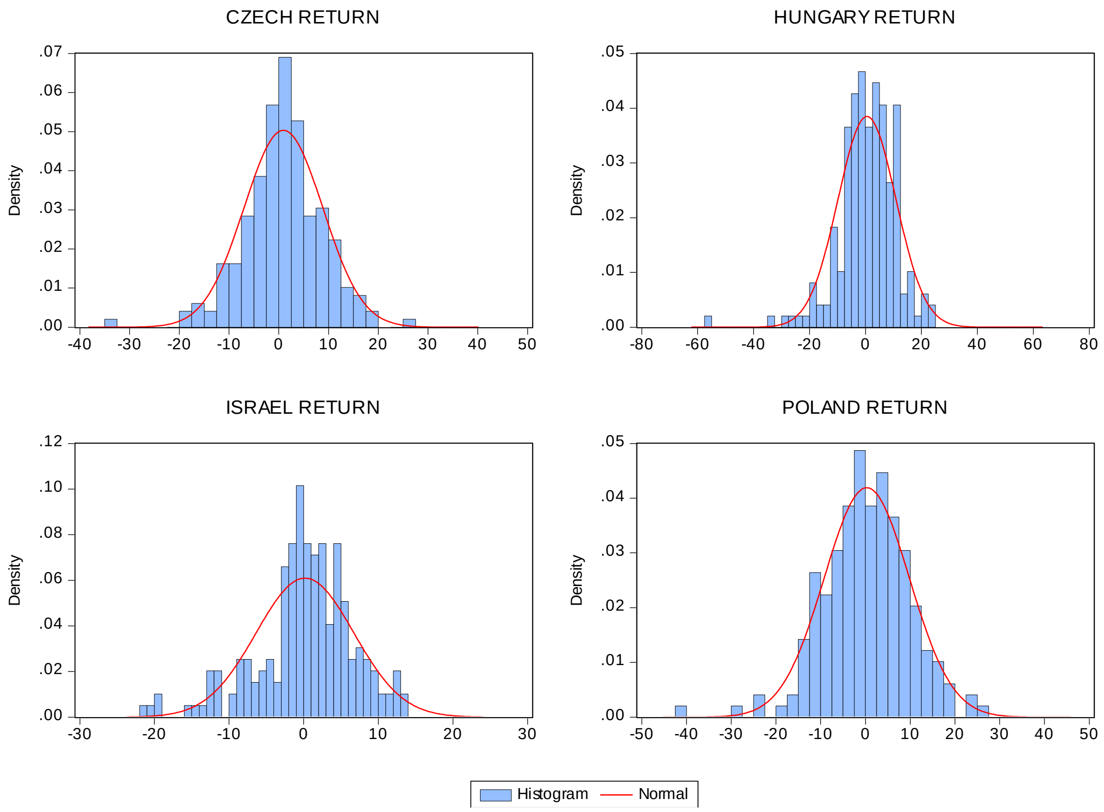
Zou, G. and Velu, R. (1999) ‘Testing mutlti-beta asset pricing models’, *Journal of Empirical Finance*, 6(1999), pp. 219-241.

9 Appendix - Return Distribution

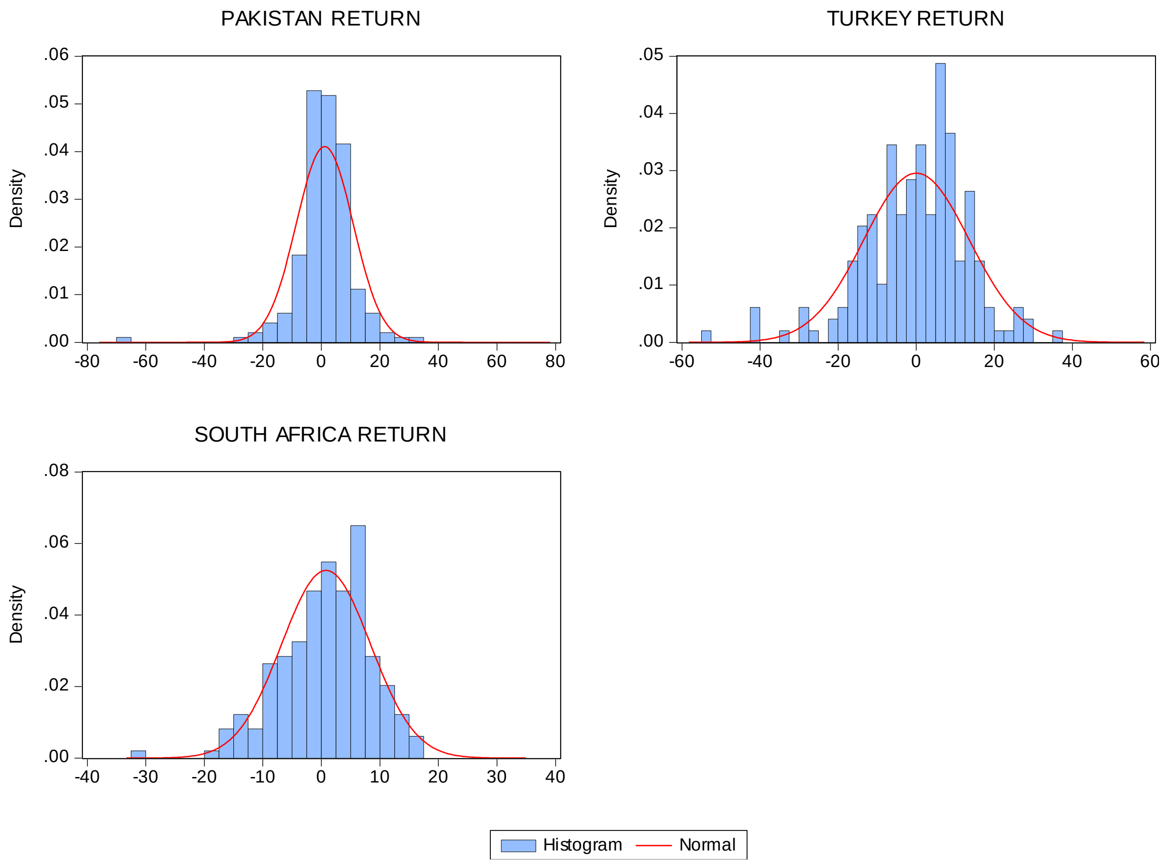
9.1 Emerging Markets Distribution of Returns Indices



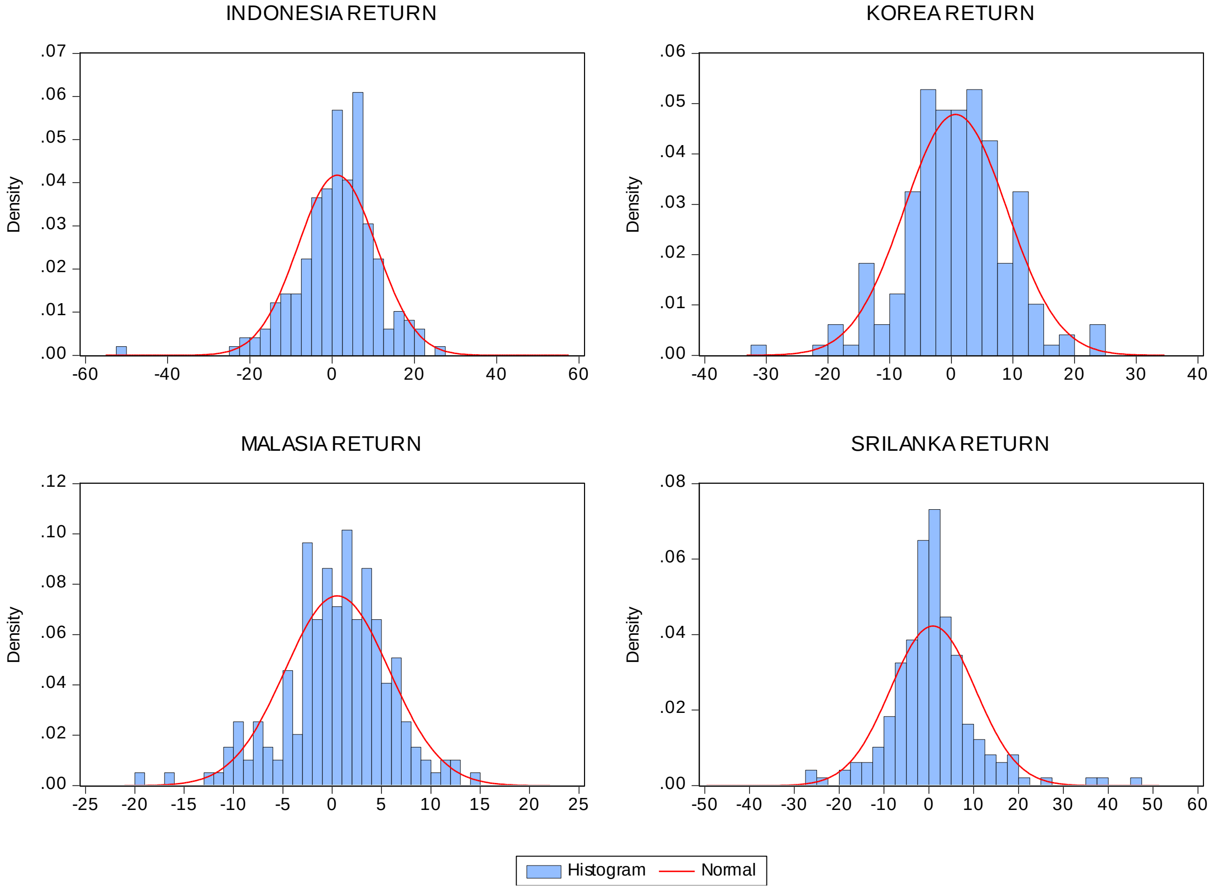
	ARGENTINA RETURN	COLOMBIA RETURN	CHILE RETURN	MEXICO RETURN
Mean	1.094097	1.494945	0.635702	0.678306
Median	1.560327	2.231005	0.56511	1.204654
Maximum	42.71755	22.25456	18.34127	15.8995
Minimum	-46.28016	-33.07771	-29.5917	-36.63701
Std. Dev.	11.83891	8.638281	6.363198	6.799446
Skewness	-0.128557	-0.40944	-0.72387	-1.032452
Kurtosis	5.461907	3.762353	5.674755	6.912616
Jarque-Bera	50.29322	10.27474	75.92912	160.6568
Probability	0	0.005873	0	0



	CZECH RETURN	HUNGARY RETURN	ISRAEL RETURN	POLAND RETURN
Mean	0.92	0.55	0.18	0.30
Median	1.28	1.24	0.54	0.13
Maximum	26.30	24.14	13.86	25.15
Minimum	-34.88	-56.83	-21.72	-41.32
Std. Dev.	7.92	10.36	6.55	9.52
Skewness	-0.42	-1.17	-0.72	-0.42
Kurtosis	4.89	7.60	4.03	4.52
Jarque-Bera	35.06	218.56	25.49	24.71
Probability	0	0	0.000003	0.000004

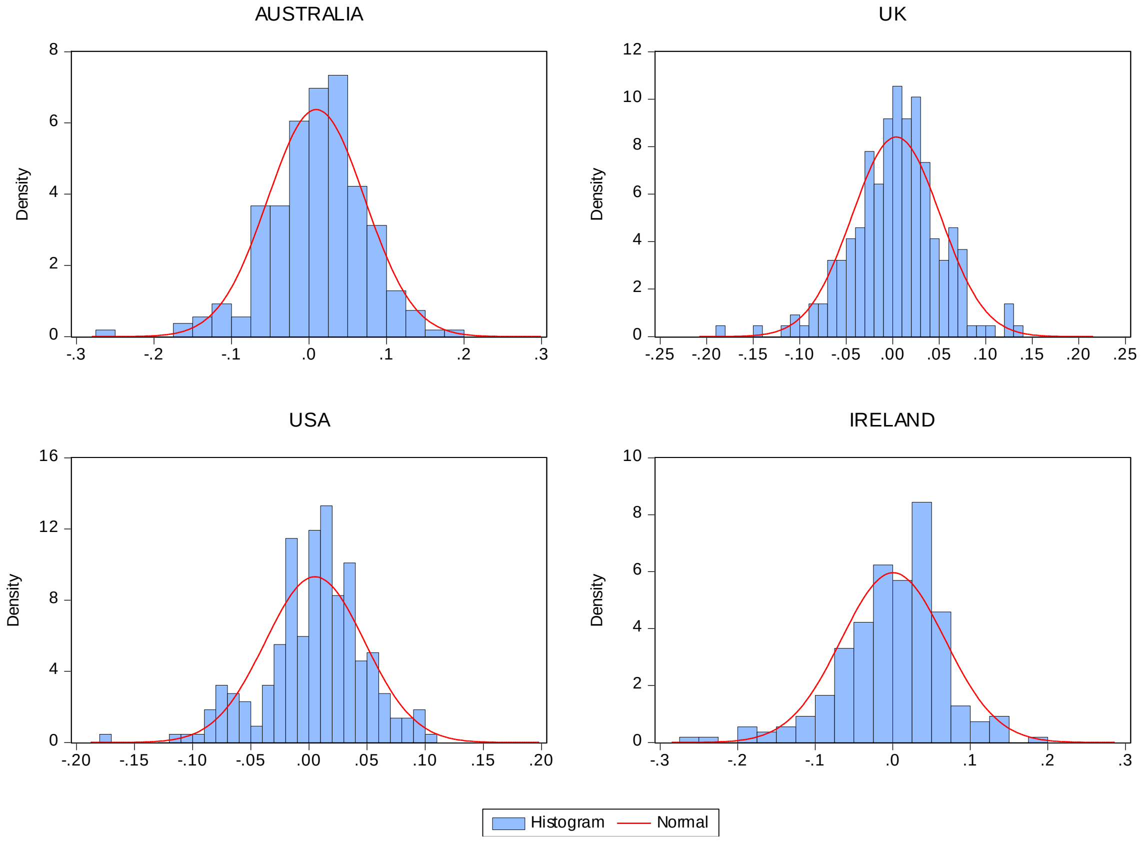


	PAKISTAN RETURN	TURKEY RETURN	SOUTH AFRICA RETURN
Mean	1.145347	0.107421	0.797685
Median	1.614059	1.480828	1.296749
Maximum	31.86474	37.07044	16.53547
Minimum	-69.2157	-53.1777	-30.35727
Std. Dev.	9.713889	13.49693	7.602987
Skewness	-1.830658	-0.66364	-0.623774
Kurtosis	16.62046	4.587956	3.717169
Jarque-Bera	1632.82	35.15866	16.99708
Probability	0	0	0.000204



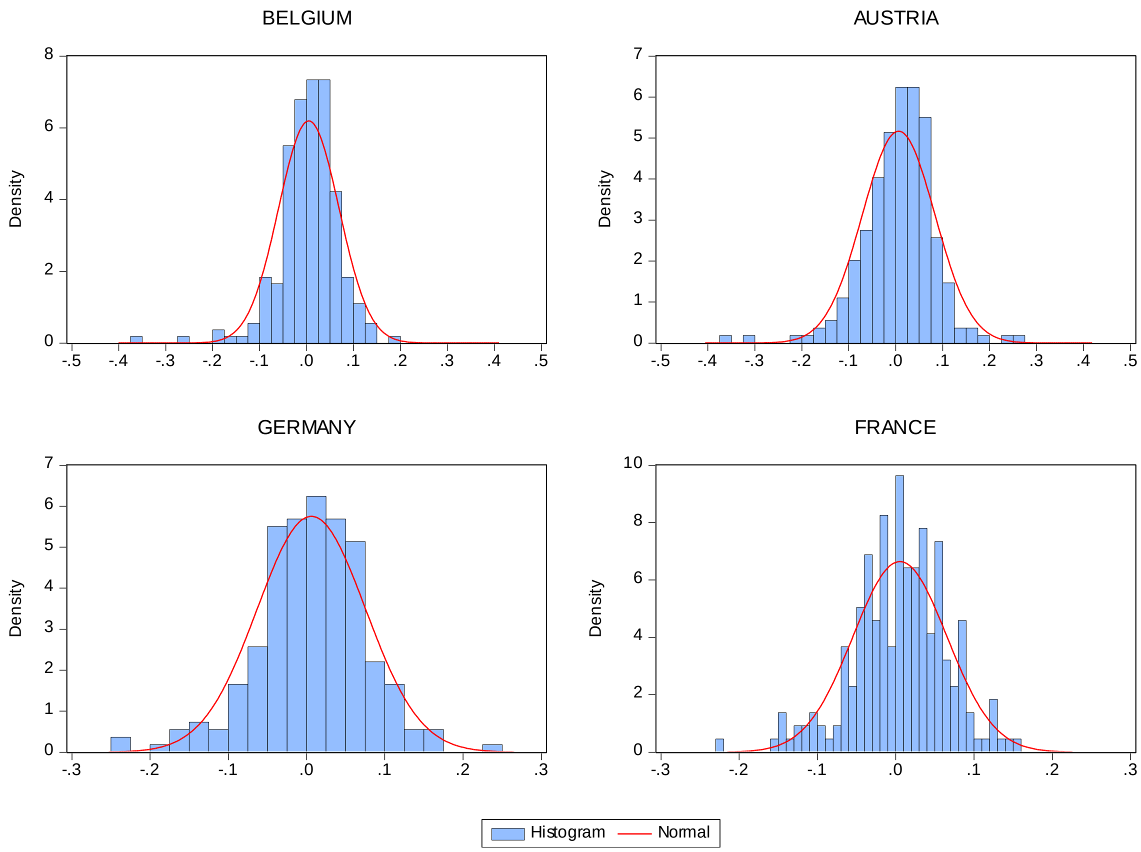
	INDONESIA RETURN	KOREA RETURN	MALAYSIA RETURN	SRILANKA RETURN
Mean	1.224181	0.699519	0.507686	0.909039
Median	1.793857	0.782667	0.869159	0.341988
Maximum	26.65364	24.31039	14.91862	47.03348
Minimum	-50.21376	-30.2758	-19.2002	-27.4694
Std. Dev.	9.552172	8.335068	5.292884	9.435726
Skewness	-0.852786	-0.21478	-0.4563	1.021698
Kurtosis	6.730921	3.914675	3.985052	7.846437
Jarque-Bera	138.136	8.381994	14.80104	227.0706
Probability	0	0.015131	0.000611	0

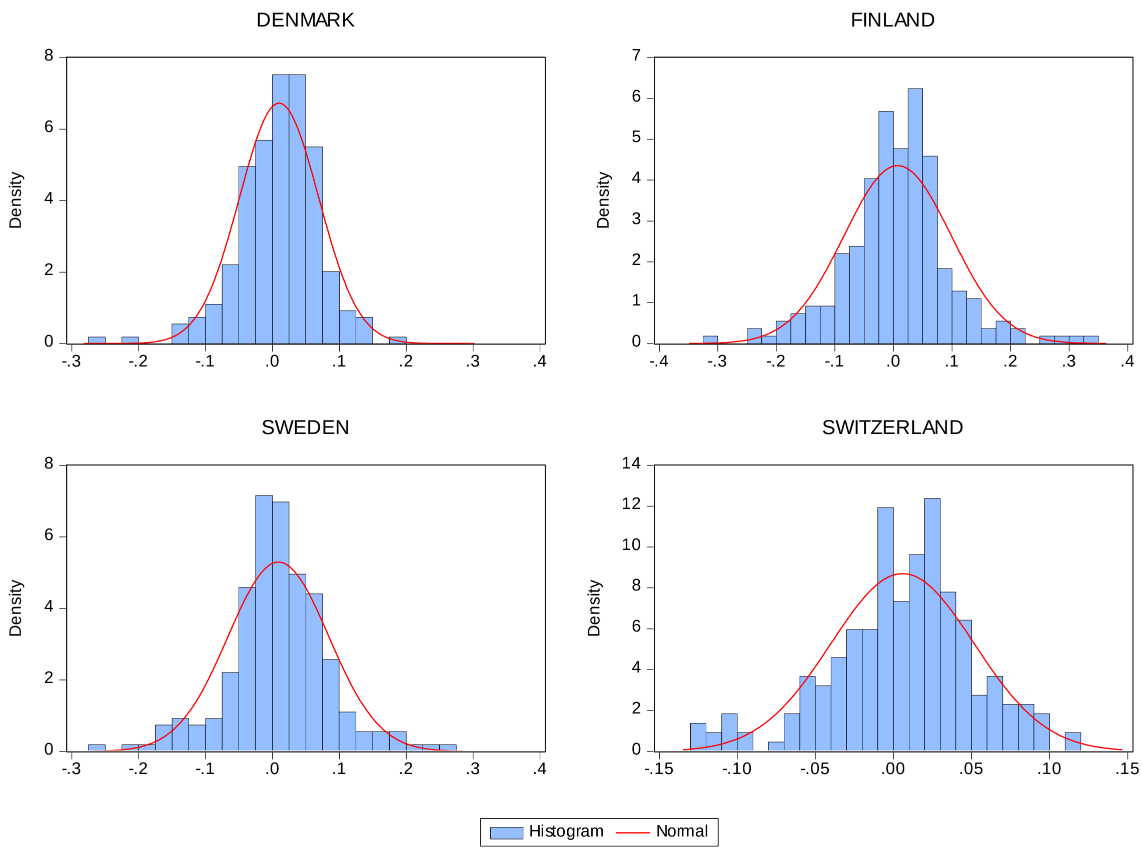
9.2 Developed Markets Distribution



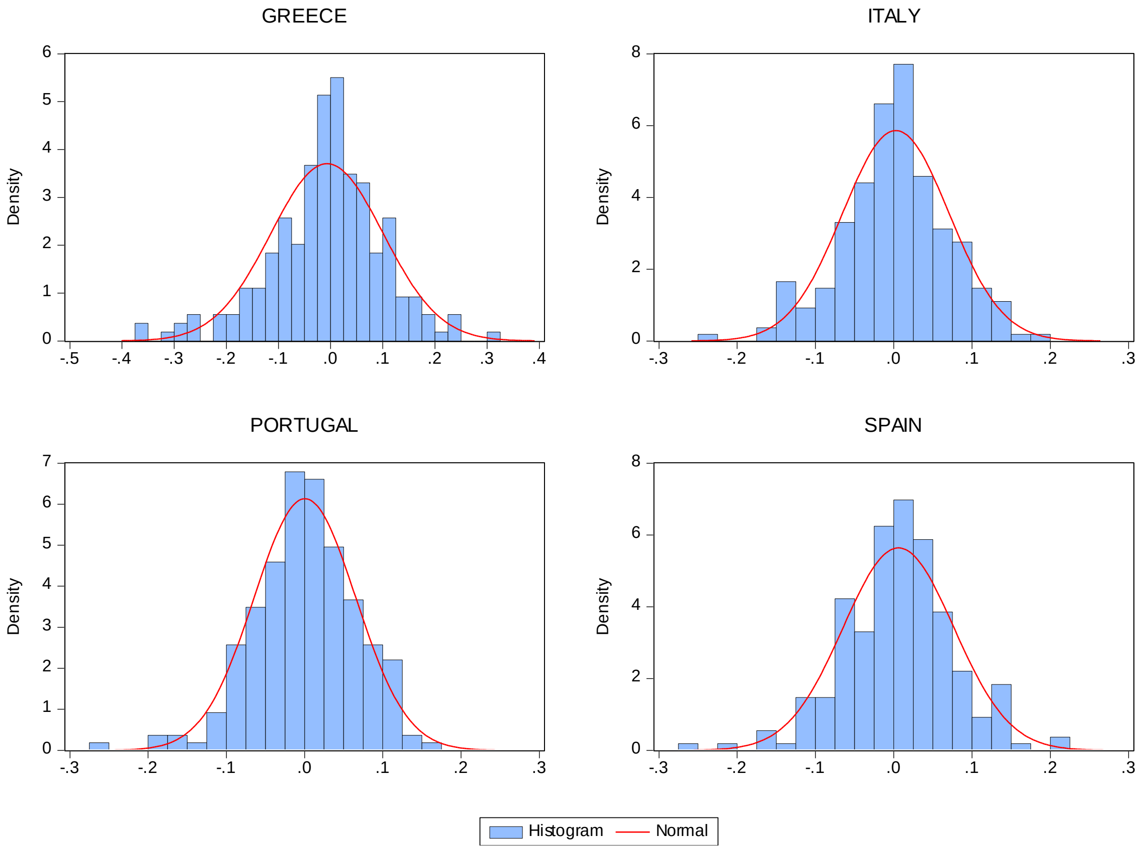
	AUSTRALIA	UK	USA	IRELAND
Mean	0.009527	0.003755	0.005175	0.000550
Median	0.011468	0.005753	0.009487	0.009082
Maximum	0.177945	0.138710	0.109866	0.192186
Minimum	-0.255098	-0.189606	-0.171016	-0.260444
Std. Dev.	0.062576	0.047447	0.042842	0.066924
Skewness	-0.481838	-0.338286	-0.518665	-0.770011
Kurtosis	4.437647	4.308956	3.990115	4.673996
Jarque-Bera	27.20911	19.72098	18.67881	46.99651
Probability	0.000001	0.000052	0.000088	0.000000

	BELGIUM	AUSTRIA	GERMANY	FRANCE
Mean	0.004776	0.006242	0.006163	0.005387
Median	0.011209	0.011943	0.008045	0.007435
Maximum	0.181905	0.255377	0.236926	0.157435
Minimum	-0.365554	-0.370410	-0.243514	-0.224143
Std. Dev.	0.064411	0.077191	0.069341	0.060063
Skewness	-1.346227	-0.796730	-0.368250	-0.425610
Kurtosis	8.702504	6.722933	4.345844	3.797784
Jarque-Bera	361.2247	148.9607	21.37971	12.36274
Probability	0.000000	0.000000	0.000023	0.002068

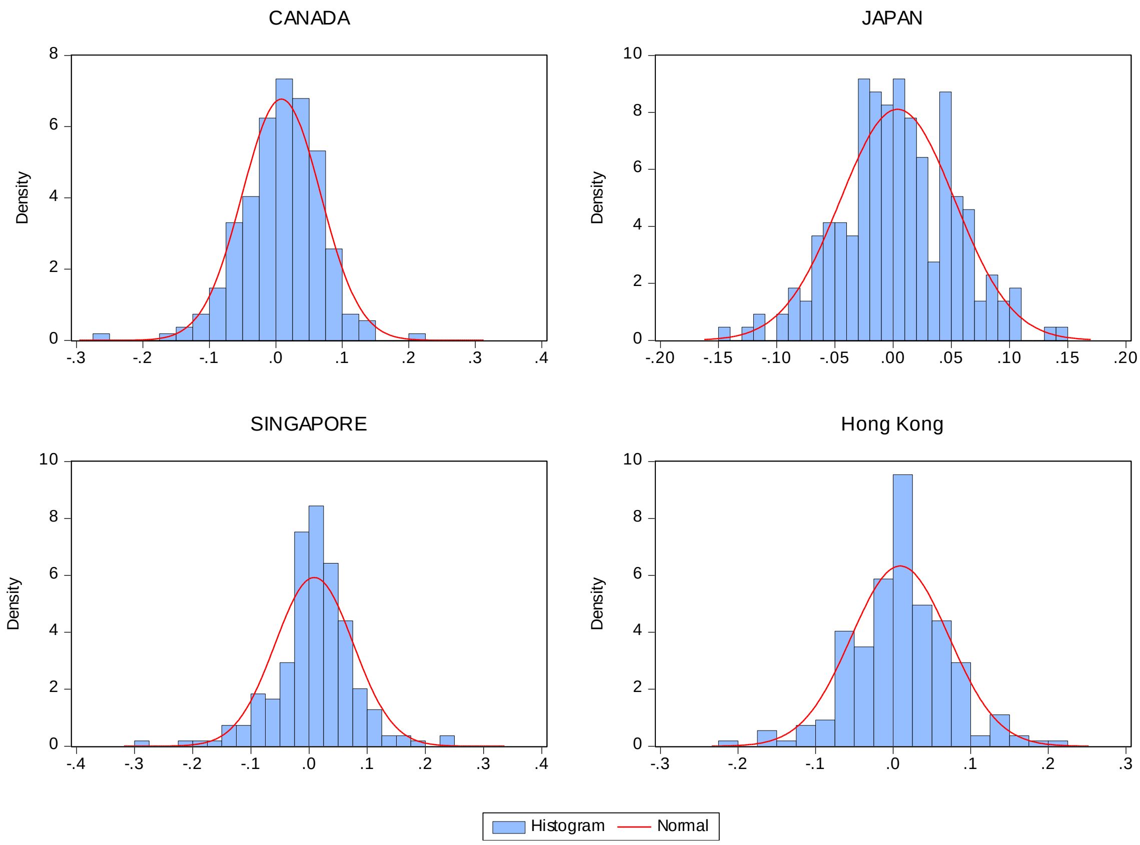

BELGIUM
AUSTRIA
GERMANY
FRANCE
Density
Histogram
Normal


DENMARK
FINLAND
SWEDEN
SWITZERLAND
Density
Histogram
Normal

	DENMARK	FINLAND	SWEDEN	SWITZERLAND
Mean	0.010106	0.007164	0.009078	0.005820
Median	0.017773	0.007350	0.006734	0.010035
Maximum	0.183420	0.332643	0.254892	0.118031
Minimum	-0.256723	-0.317578	-0.266556	-0.122668
Std. Dev.	0.059330	0.091602	0.075362	0.045864
Skewness	-0.661289	0.104617	-0.121447	-0.463678
Kurtosis	5.121553	4.791197	4.577204	3.485014
Jarque-Bera	56.77264	29.54050	23.13135	9.948331
Probability	0.000000	0.000000	0.000009	0.006914

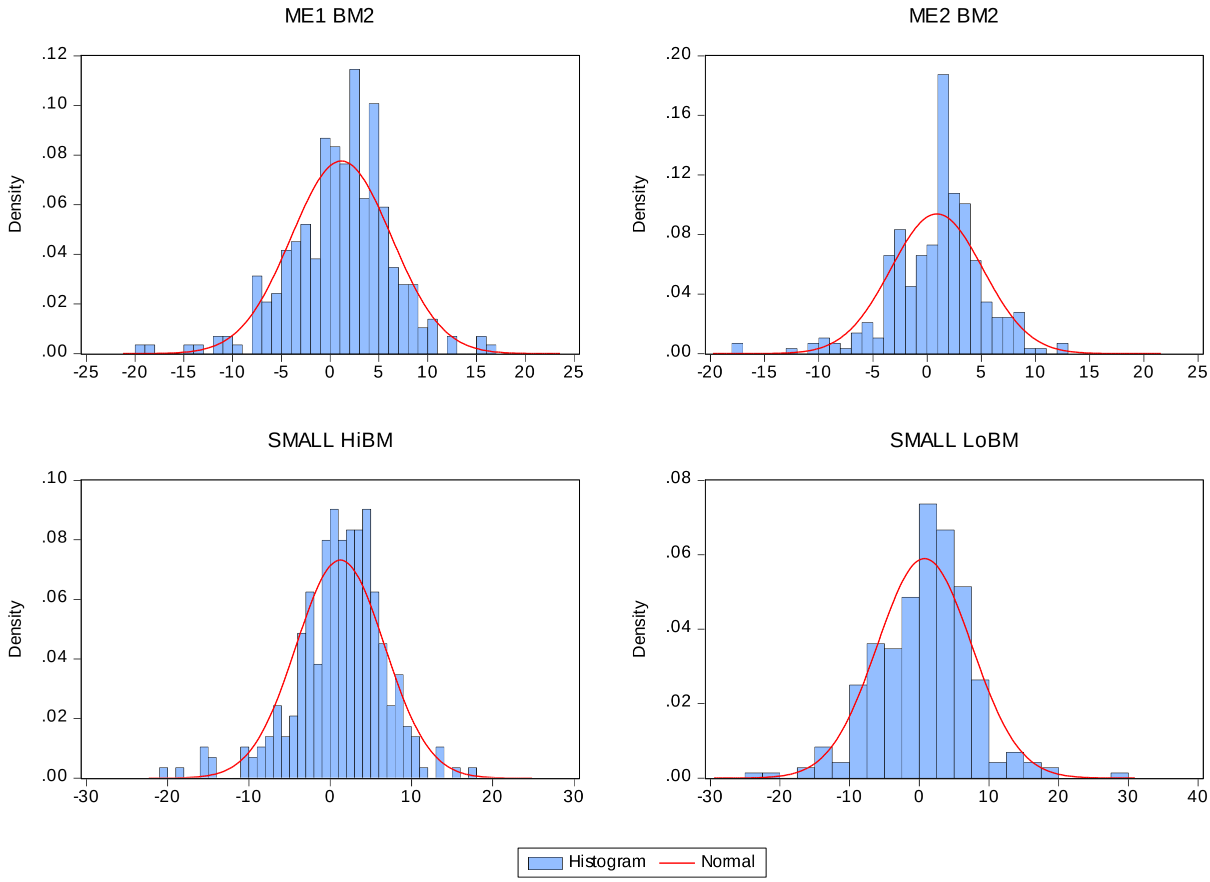


	GREECE	ITALY	PORTUGAL	SPAIN
Mean	-0.006907	0.002697	0.000493	0.006070
Median	-1.38E-05	0.005650	0.001918	0.011277
Maximum	0.307048	0.191572	0.157702	0.220930
Minimum	-0.367031	-0.236006	-0.262496	-0.252685
Std. Dev.	0.107747	0.068066	0.065041	0.070757
Skewness	-0.413021	-0.226130	-0.432289	-0.170480
Kurtosis	3.995059	3.449022	3.868704	3.917169
Jarque-Bera	15.19177	3.689287	13.64446	8.696861
Probability	0.000503	0.158082	0.001089	0.012927



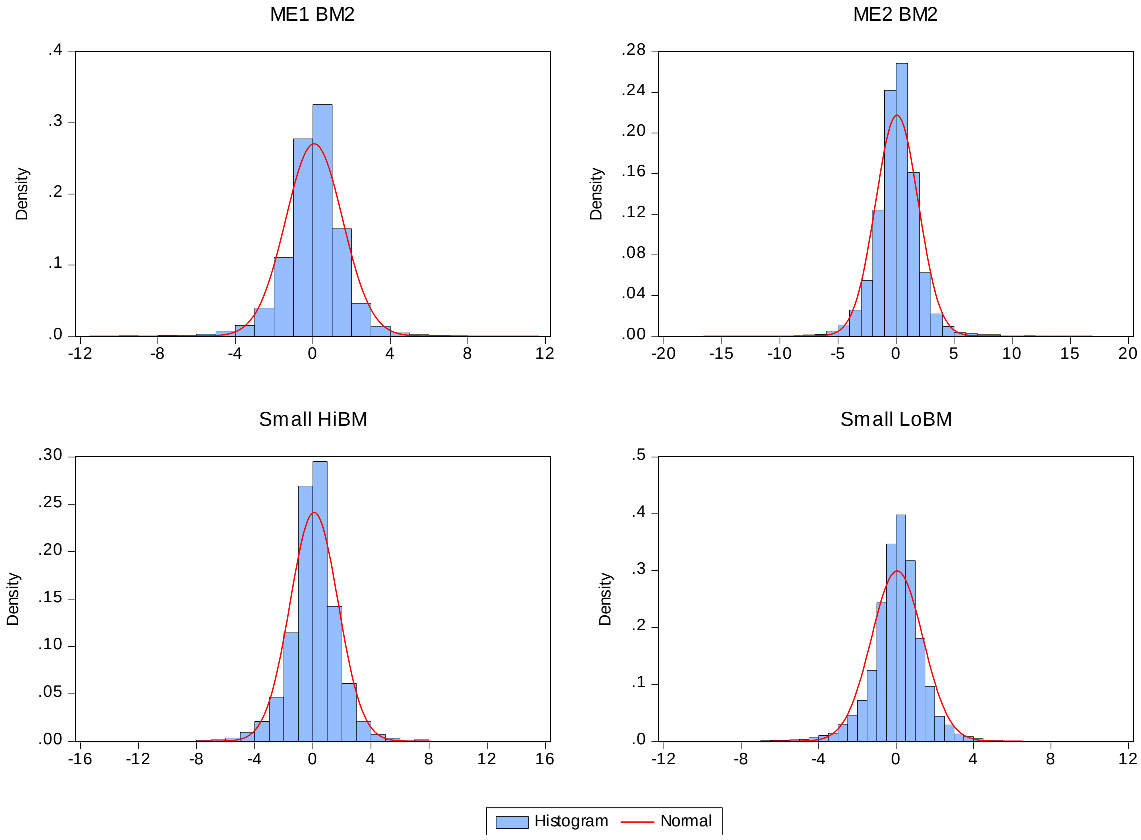
	CANADA	JAPAN	SINGAPORE	HONG_KONG
Mean	0.008450	0.003790	0.008909	0.009113
Median	0.011301	0.003765	0.009186	0.009466
Maximum	0.212631	0.142783	0.248566	0.223526
Minimum	-0.269431	-0.147818	-0.289926	-0.212749
Std. Dev.	0.058894	0.049202	0.067325	0.063040
Skewness	-0.519470	-0.049335	-0.347714	-0.073971
Kurtosis	5.191781	3.120142	5.858769	4.155159
Jarque-Bera	53.44000	0.219541	78.62696	12.31953
Probability	0.000000	0.896040	0.000000	0.002113

9.3 Return Distribution Portfolios US



Measures US	_3_PORTFOLIO	_4_PORTFOLIO	_5_PORTFOLIO	_6_PORTFOLIO
Mean	1.265064	0.967477	1.475543	0.965764
Median	1.525000	1.210000	1.640000	1.160000
Maximum	62.20000	51.89000	83.58000	59.94000
Minimum	-30.05000	-28.15000	-33.83000	-32.39000
Std. Dev.	7.000089	5.684008	8.174609	7.544220
Skewness	1.220687	1.284336	2.132736	0.690181
Kurtosis	17.14174	20.70470	24.91087	10.73591
Jarque-Bera	9319.191	14482.46	22547.19	2794.173
Probability	0.000000	0.000000	0.000000	0.000000

9.4 Return Distribution India

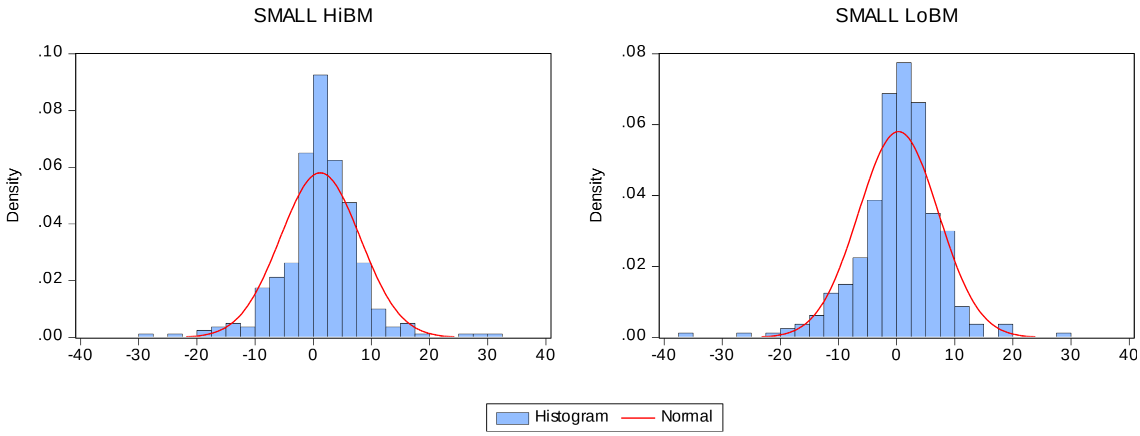


Measure - India	_3_PORTFOLIO	_4_PORTFOLIO	_5_PORTFOLIO	_6_PORTFOLIO
Mean	0.070372	0.078291	0.088067	0.057199
Median	0.122324	0.117550	0.108364	0.119178
Maximum	9.398864	15.29360	14.57784	7.328993
Minimum	-10.52736	-14.39534	-10.35712	-10.23488
Std. Dev.	1.473550	1.832137	1.651459	1.332357
Skewness	-0.433208	-0.008243	-0.014561	-0.549566
Kurtosis	7.061996	8.185315	6.882381	7.169669
Jarque-Bera	4091.240	6376.881	3574.986	4409.932
Probability	0.000000	0.000000	0.000000	0.000000

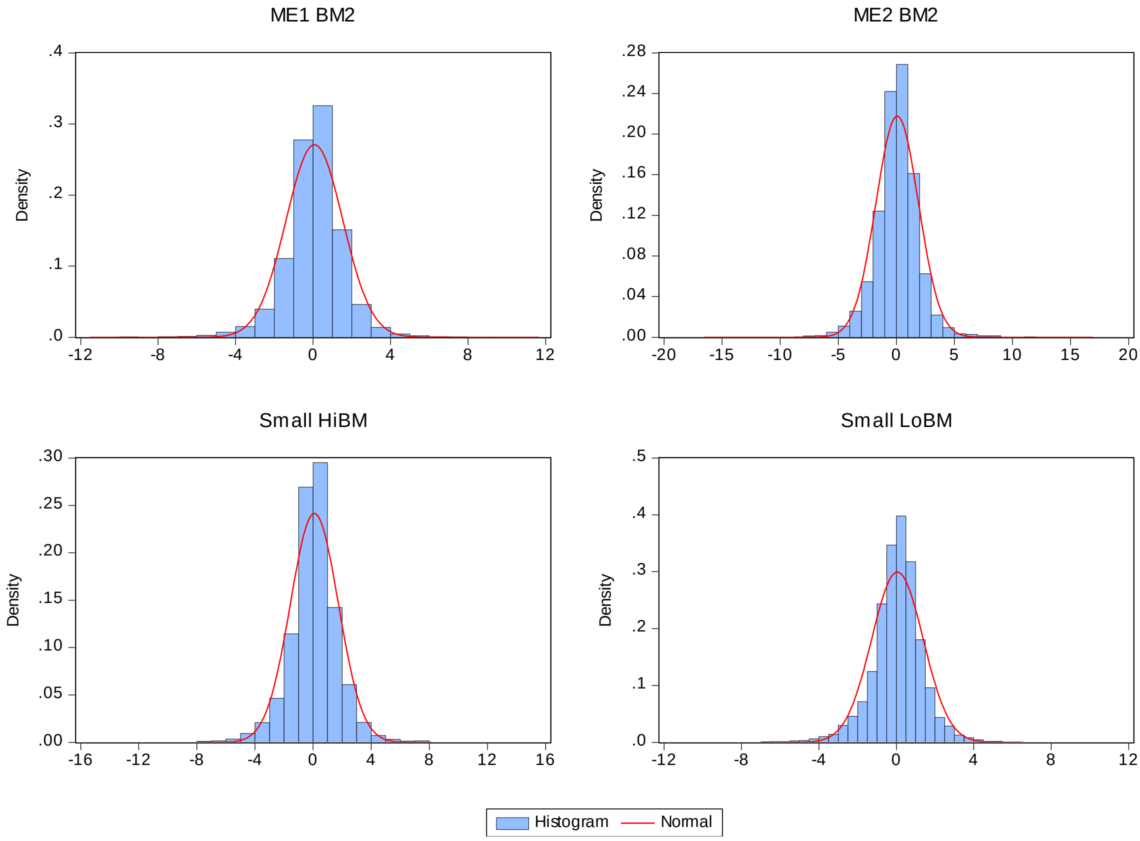
9.5 Asia Pacific Return Distribution

	Small HiBM	Small LoBM
Mean	1.211438	0.325719
Median	1.295000	0.685000
Maximum	31.46000	28.91000
Minimum	-29.83000	-35.65000
Std. Dev.	6.873976	6.870262
Skewness	-0.119203	-0.653509

Kurtosis	6.702747	6.472221
Jarque-Bera	183.5623	183.5282
Probability	0.000000	0.000000



9.6 Return Distribution India



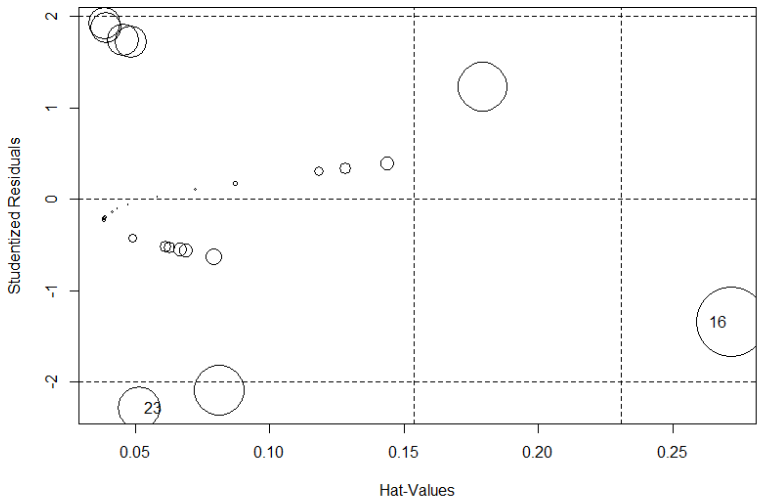
Measure - India	_3_PORTFOLIO	_4_PORTFOLIO	_5_PORTFOLIO	_6_PORTFOLIO
Mean	0.070372	0.078291	0.088067	0.057199
Median	0.122324	0.117550	0.108364	0.119178
Maximum	9.398864	15.29360	14.57784	7.328993
Minimum	-10.52736	-14.39534	-10.35712	-10.23488

Std. Dev.	1.473550	1.832137	1.651459	1.332357
Skewness	-0.433208	-0.008243	-0.014561	-0.549566
Kurtosis	7.061996	8.185315	6.882381	7.169669
Jarque-Bera	4091.240	6376.881	3574.986	4409.932
Probability	0.000000	0.000000	0.000000	0.000000

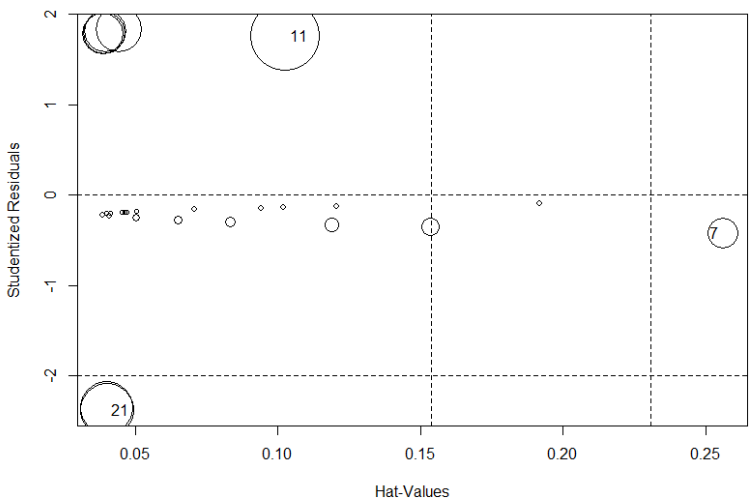
9.7 Outlier Identification Cook's test

9.7.1 Emerging Markets

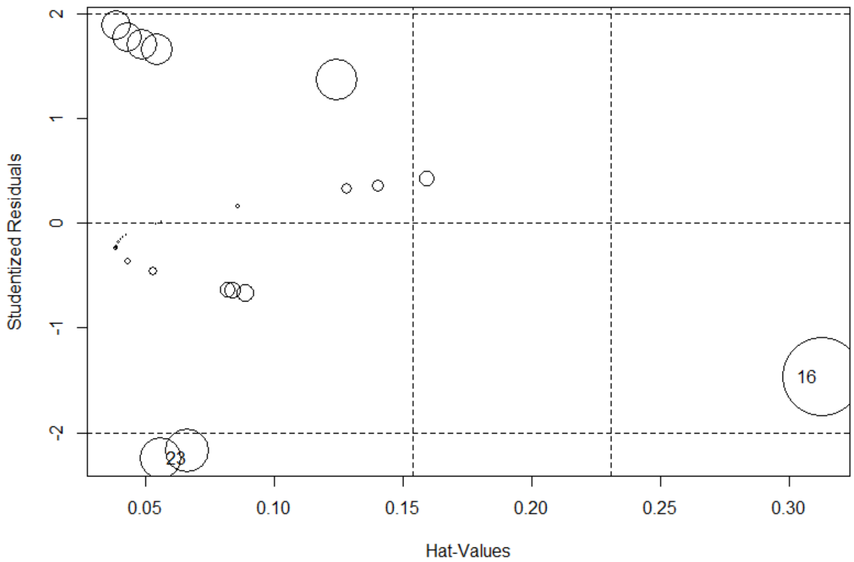
Standard deviation vs. Mean Returns:



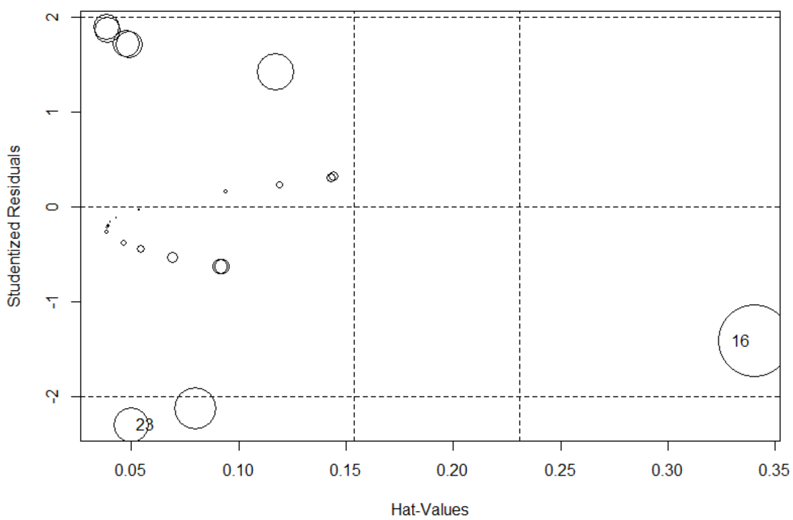
Beta vs. Mean Return:



Semideviation vs. Mean returns:

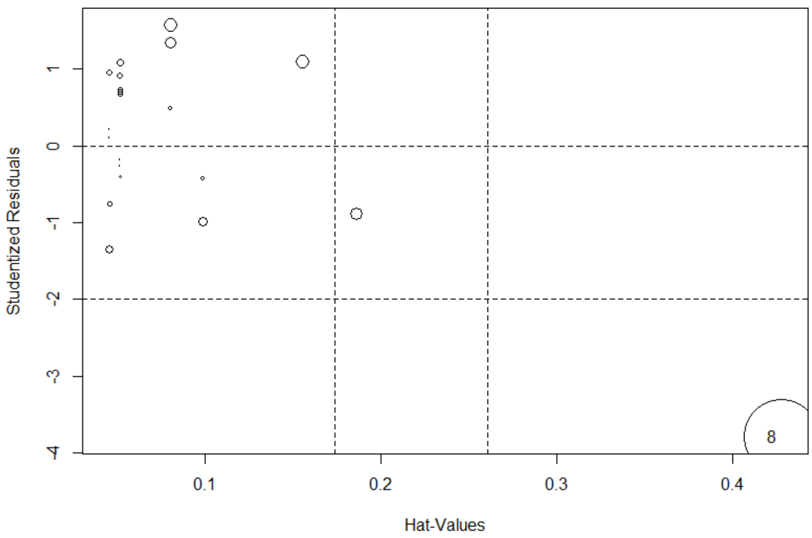


Downside Beta vs. Mean Returns:

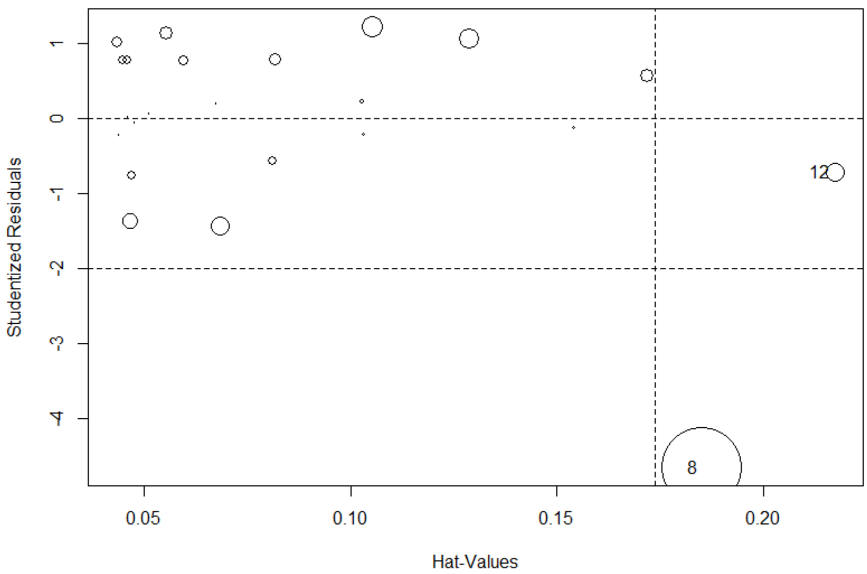


9.7.2 Developed Markets

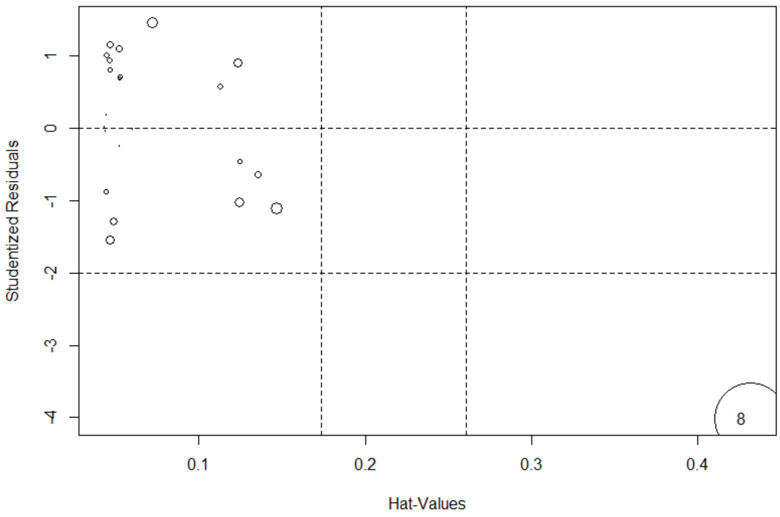
Standard deviation vs. Mean Returns:



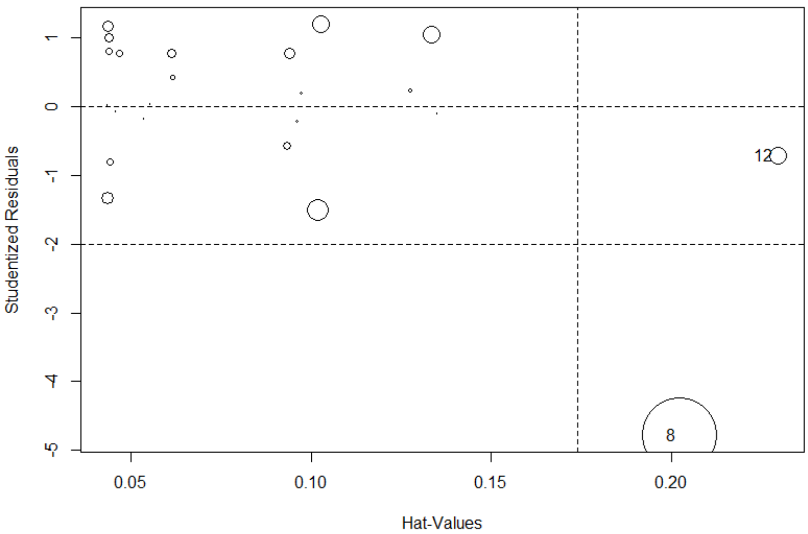
Beta vs. Mean Return:



Semideviation vs. Mean returns:



Downside Beta vs. Mean Returns:



9.8 Heteroskedasticity test

Portfolio 2 US

Heteroskedasticity Test: White

F-statistic	156.3346	Prob. F(2,1083)	0.0000
Obs*R-squared	243.2946	Prob. Chi-Square(2)	0.0000
Scaled explained SS	484.9472	Prob. Chi-Square(2)	0.0000

Portfolio 3 US

Heteroskedasticity Test: White

F-statistic	51.93408	Prob. F(2,1083)	0.0000
Obs*R-squared	95.04074	Prob. Chi-Square(2)	0.0000
Scaled explained SS	1280.168	Prob. Chi-Square(2)	0.0000

Portfolio 4 US

Heteroskedasticity Test: White

F-statistic	450.0521	Prob. F(2,1083)	0.0000
Obs*R-squared	492.9207	Prob. Chi-Square(2)	0.0000
Scaled explained SS	4250.216	Prob. Chi-Square(2)	0.0000

Portfolio 5 US

Heteroskedasticity Test: White

F-statistic	149.5574	Prob. F(2,1083)	0.0000
Obs*R-squared	235.0302	Prob. Chi-Square(2)	0.0000
Scaled explained SS	2887.340	Prob. Chi-Square(2)	0.0000

Portfolio 6 US

Heteroskedasticity Test: White

F-statistic	31.46095	Prob. F(2,1083)	0.0000
Obs*R-squared	59.63162	Prob. Chi-Square(2)	0.0000
Scaled explained SS	429.9668	Prob. Chi-Square(2)	0.0000

Portfolio 1 India

Heteroskedasticity Test: White

F-statistic	22.28254	Prob. F(2,5173)	0.0000
Obs*R-squared	44.21007	Prob. Chi-Square(2)	0.0000
Scaled explained SS	304.4247	Prob. Chi-Square(2)	0.0000

Portfolio 2 India

Heteroskedasticity Test: White

F-statistic	121.5795	Prob. F(2,5689)	0.0000
Obs*R-squared	233.3149	Prob. Chi-Square(2)	0.0000
Scaled explained SS	1057.300	Prob. Chi-Square(2)	0.0000

Portfolio 3 - India
Heteroskedasticity Test: White

F-statistic	320.3986	Prob. F(2,5689)	0.0000
Obs*R-squared	576.2298	Prob. Chi-Square(2)	0.0000
Scaled explained SS	1718.719	Prob. Chi-Square(2)	0.0000

Portfolio 4 -India
Heteroskedasticity Test: White

F-statistic	101.1066	Prob. F(2,5689)	0.0000
Obs*R-squared	195.3753	Prob. Chi-Square(2)	0.0000
Scaled explained SS	998.3417	Prob. Chi-Square(2)	0.0000

Portfolio 5 -India
Heteroskedasticity Test: White

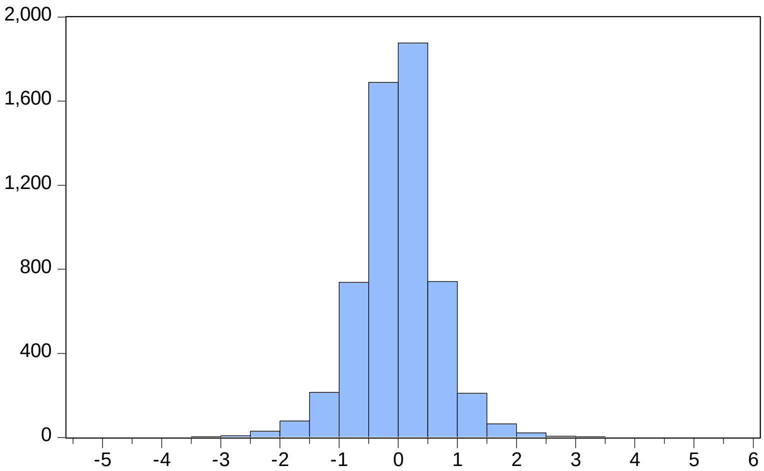
F-statistic	288.6877	Prob. F(2,5689)	0.0000
Obs*R-squared	524.4532	Prob. Chi-Square(2)	0.0000
Scaled explained SS	2058.615	Prob. Chi-Square(2)	0.0000

Portfolio 6 - India
Heteroskedasticity Test: White

F-statistic	375.8553	Prob. F(2,5689)	0.0000
Obs*R-squared	664.3269	Prob. Chi-Square(2)	0.0000
Scaled explained SS	1920.832	Prob. Chi-Square(2)	0.0000

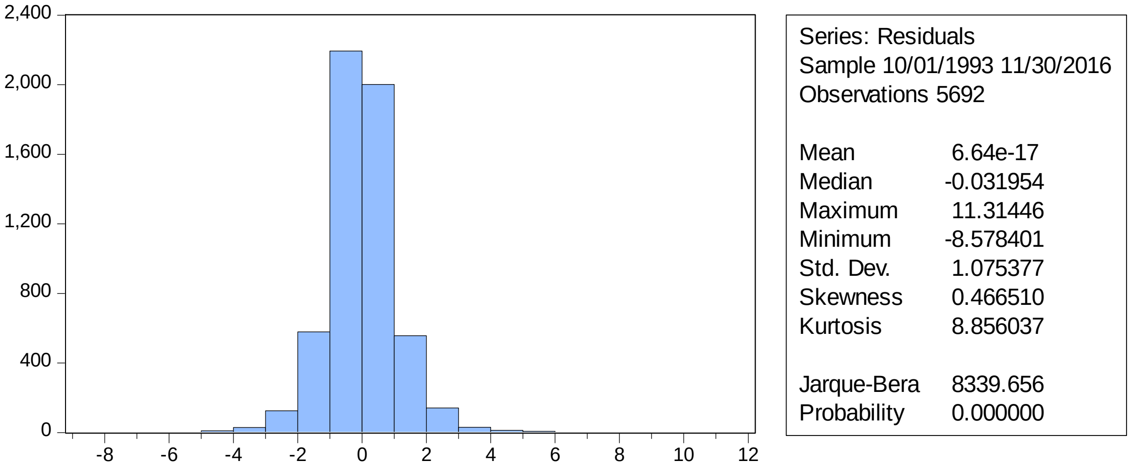
9.9 Test for Normality of the Residuals

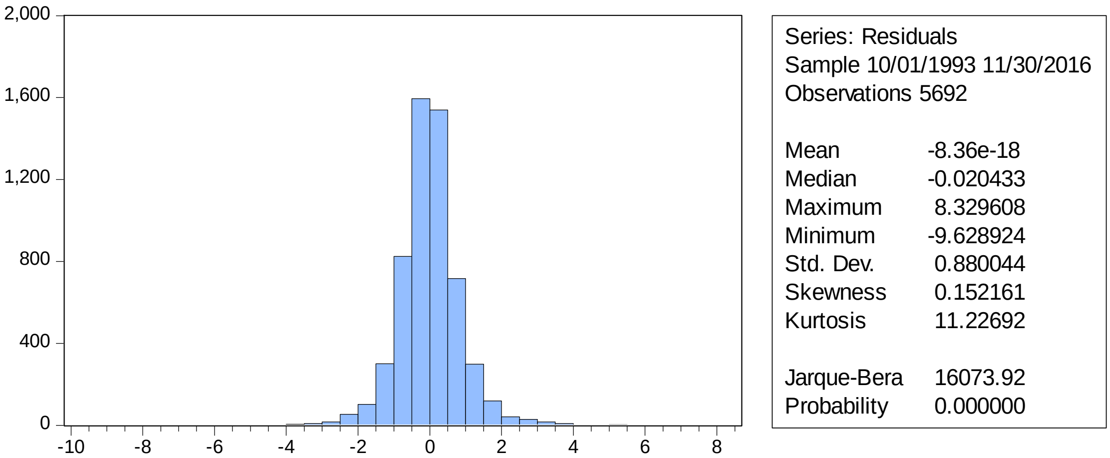
9.9.1 India

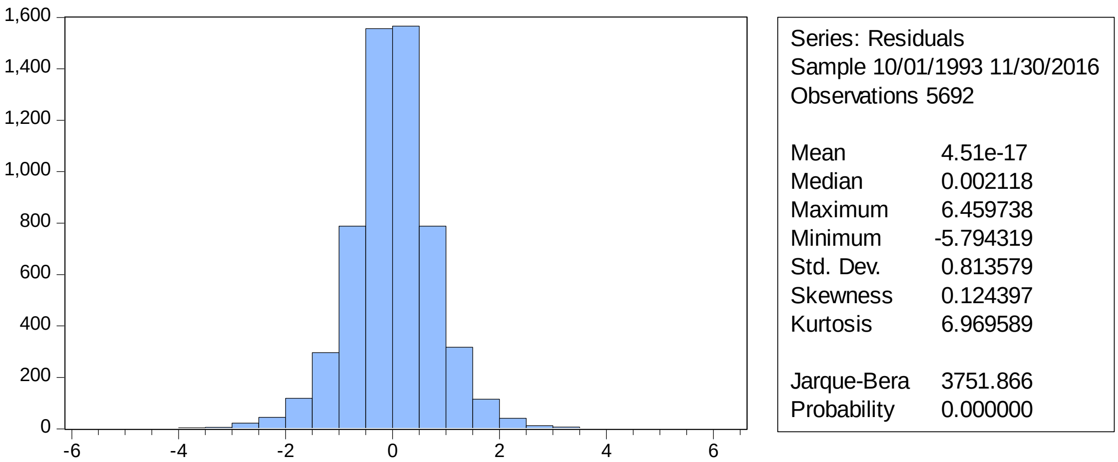


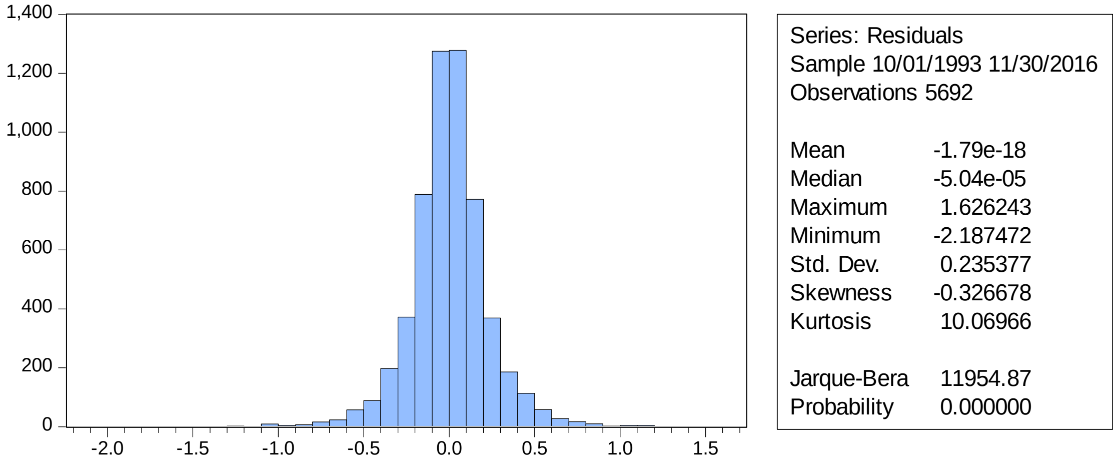
Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5692

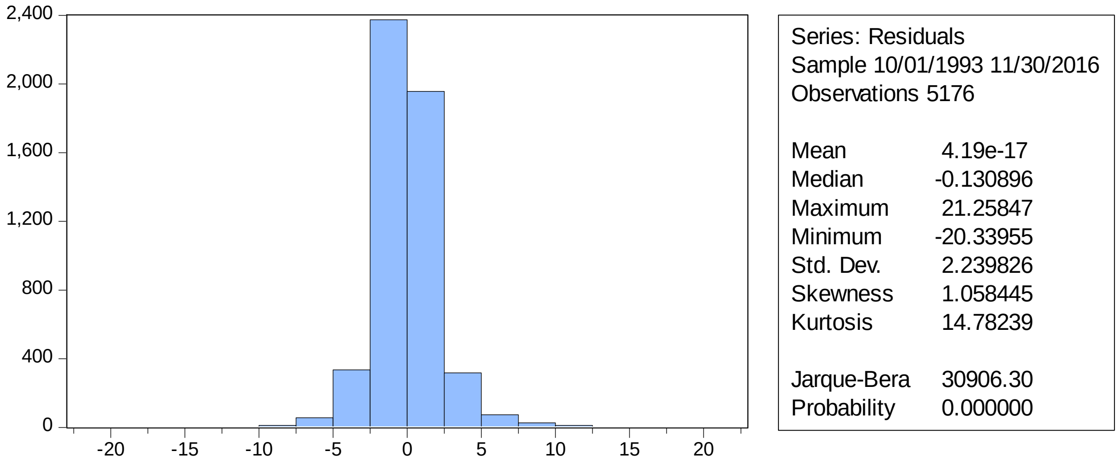
Mean	9.15e-18
Median	0.021364
Maximum	5.919179
Minimum	-5.237954
Std. Dev.	0.674096
Skewness	-0.039422
Kurtosis	6.786859
Jarque-Bera	3402.515
Probability	0.000000


Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5692
Mean 6.64e-17
Median -0.031954
Maximum 11.31446
Minimum -8.578401
Std. Dev. 1.075377
Skewness 0.466510
Kurtosis 8.856037
Jarque-Bera 8339.656
Probability 0.000000

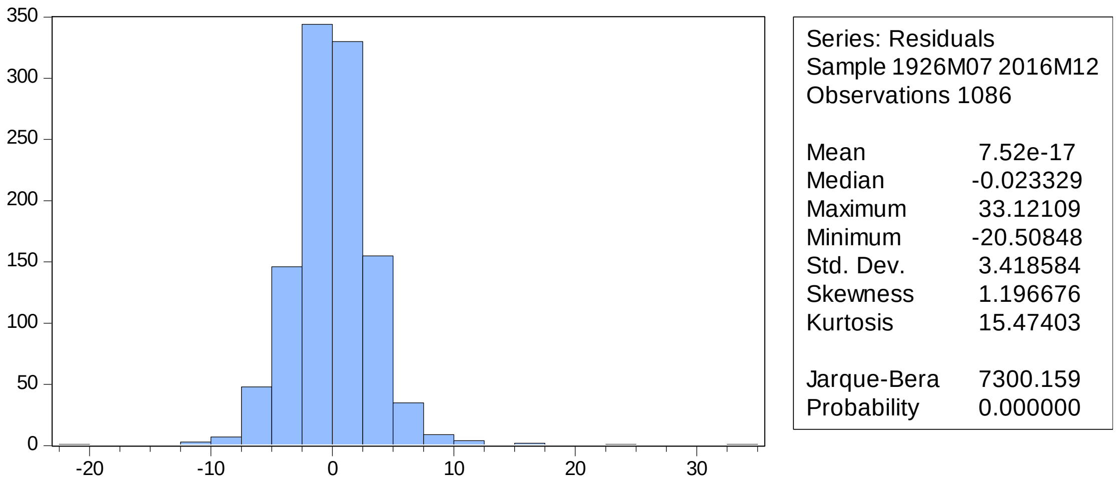

Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5692
Mean -8.36e-18
Median -0.020433
Maximum 8.329608
Minimum -9.628924
Std. Dev. 0.880044
Skewness 0.152161
Kurtosis 11.22692
Jarque-Bera 16073.92
Probability 0.000000

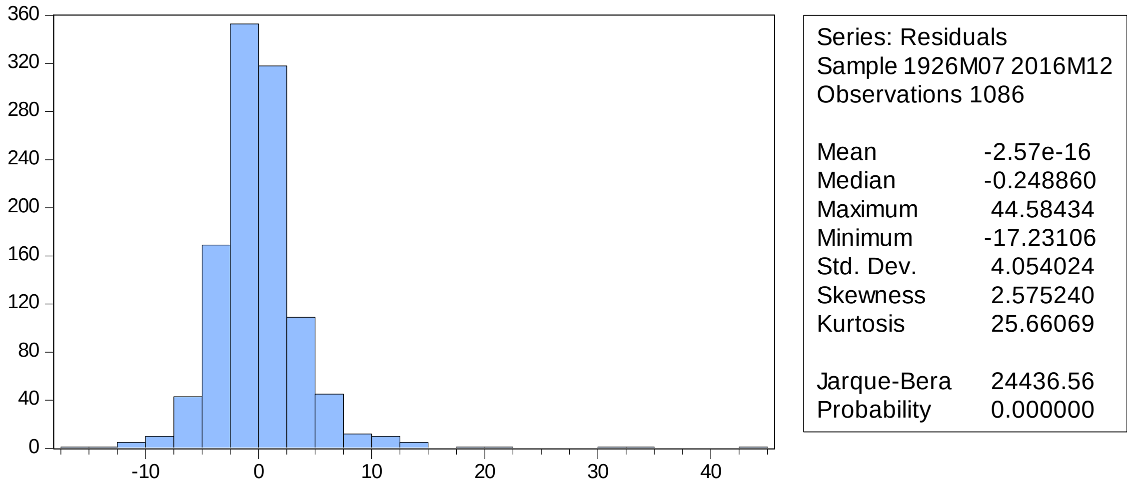

Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5692
Mean 4.51e-17
Median 0.002118
Maximum 6.459738
Minimum -5.794319
Std. Dev. 0.813579
Skewness 0.124397
Kurtosis 6.969589
Jarque-Bera 3751.866
Probability 0.000000

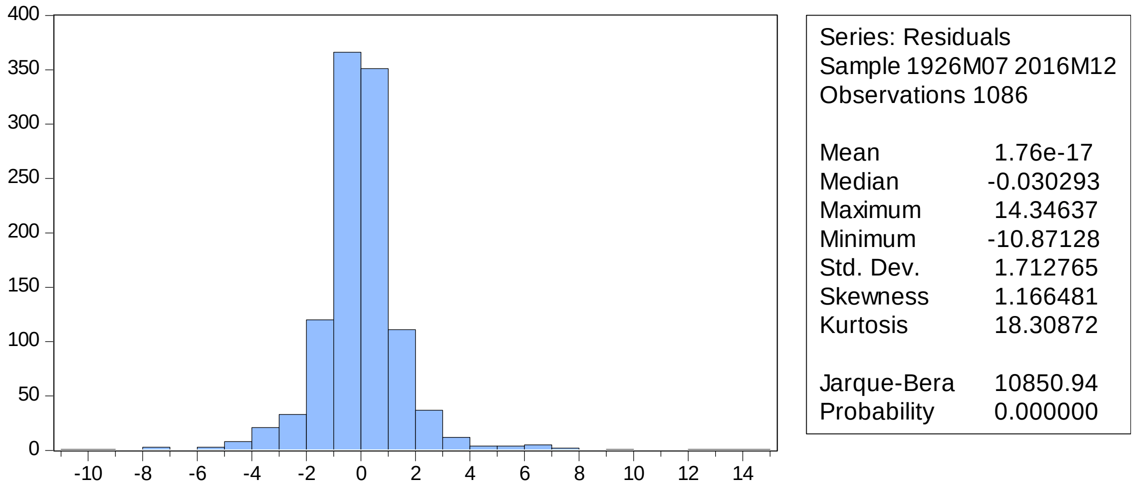

Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5692
Mean -1.79e-18
Median -5.04e-05
Maximum 1.626243
Minimum -2.187472
Std. Dev. 0.235377
Skewness -0.326678
Kurtosis 10.06966
Jarque-Bera 11954.87
Probability 0.000000

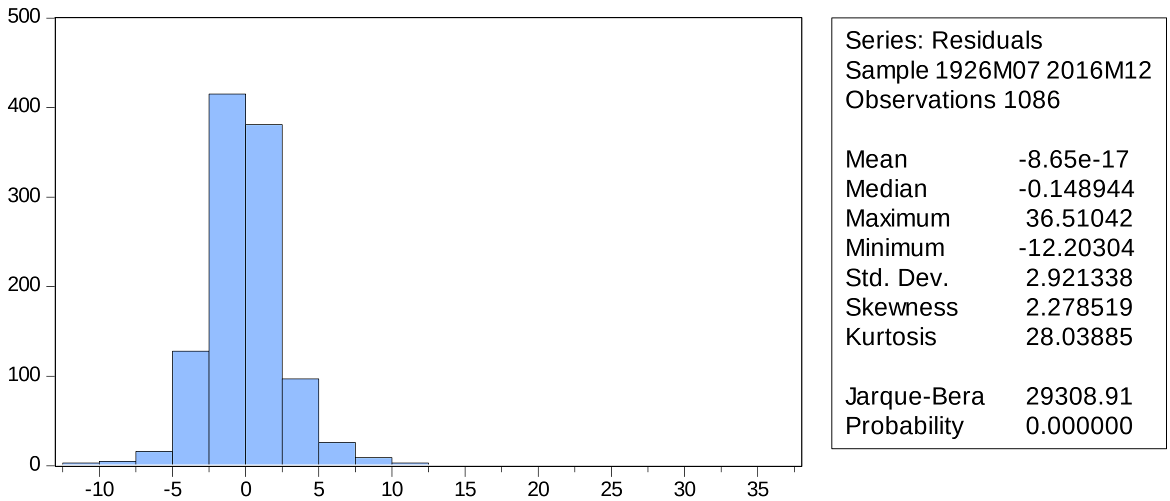

Series: Residuals
Sample 10/01/1993 11/30/2016
Observations 5176
Mean 4.19e-17
Median -0.130896
Maximum 21.25847
Minimum -20.33955
Std. Dev. 2.239826
Skewness 1.058445
Kurtosis 14.78239
Jarque-Bera 30906.30
Probability 0.000000

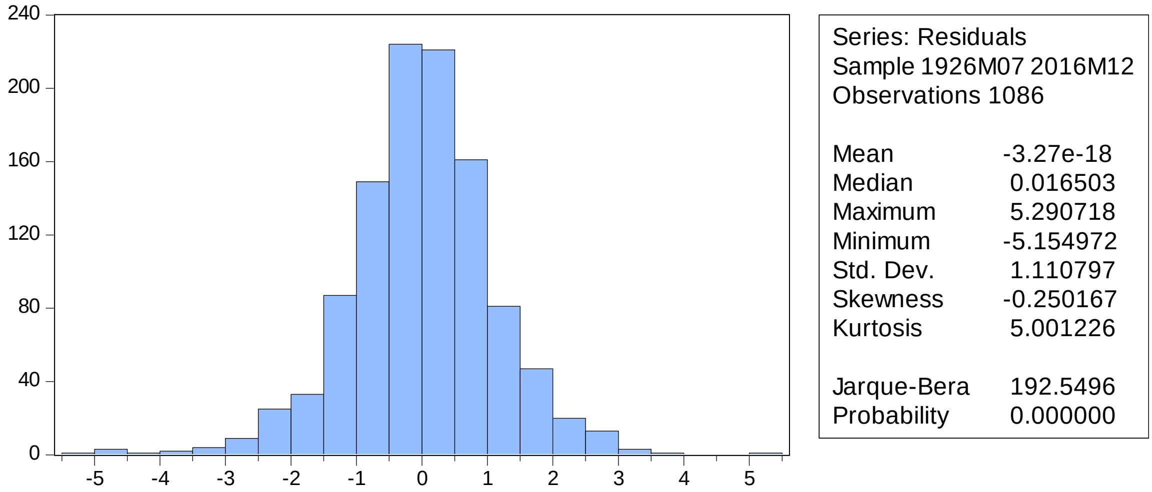
9.9.2 US

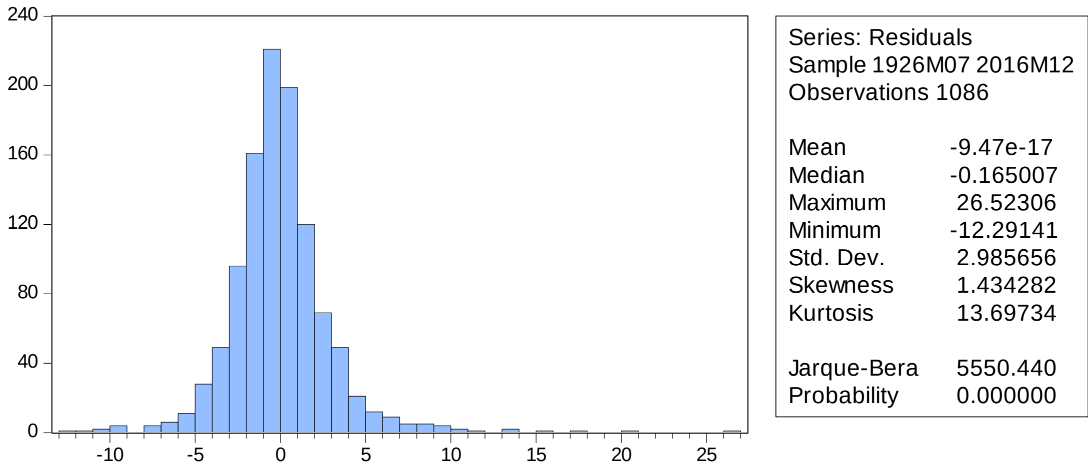

Series: Residuals
Sample 1926M07 2016M12
Observations 1086
Mean 7.52e-17
Median -0.023329
Maximum 33.12109
Minimum -20.50848
Std. Dev. 3.418584
Skewness 1.196676
Kurtosis 15.47403
Jarque-Bera 7300.159
Probability 0.000000


Series: Residuals
Sample 1926M07 2016M12
Observations 1086
Mean -2.57e-16
Median -0.248860
Maximum 44.58434
Minimum -17.23106
Std. Dev. 4.054024
Skewness 2.575240
Kurtosis 25.66069
Jarque-Bera 24436.56
Probability 0.000000


Series: Residuals
Sample 1926M07 2016M12
Observations 1086
Mean 1.76e-17
Median -0.030293
Maximum 14.34637
Minimum -10.87128
Std. Dev. 1.712765
Skewness 1.166481
Kurtosis 18.30872
Jarque-Bera 10850.94
Probability 0.000000


Series: Residuals
Sample 1926M07 2016M12
Observations 1086
Mean -8.65e-17
Median -0.148944
Maximum 36.51042
Minimum -12.20304
Std. Dev. 2.921338
Skewness 2.278519
Kurtosis 28.03885
Jarque-Bera 29308.91
Probability 0.000000





9.10 Time Series Test Results

9.10.1 US Portfolios

Eq Name:			**Period 1**			
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.111558 [0.3516]	0.121483 [1.2249]	0.277216 [0.8878]	-0.062167 [-0.3694]	0.370218 [0.7963]	0.138506 [0.4219]
MKT_RF	1.435695 [21.3749]**	0.932288 [47.4657]**	1.305382 [19.9879]**	1.124533 [24.5409]**	1.563968 [14.8781]**	1.222162 [18.8672]**

Eq Name:	Period 2					
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.113347	-0.093379	0.063819	0.137939	0.225618	-0.089182
	[0.7636]	[-1.6686]	[0.4806]	[2.5368]*	[1.1240]	[-0.6306]
MKT_RF	1.226259	0.978087	1.103123	0.947102	1.296975	1.036629
	[31.9215]**	[64.9696]**	[28.0328]**	[62.6390]**	[19.9959]**	[24.5410]**

Eq Name:	Period 3					
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.383420	-0.013926	0.107826	0.032821	0.348698	-0.232893
	[2.9374]**	[-0.1936]	[0.6952]	[0.3758]	[1.9703]	[-1.0878]
MKT_RF	1.036408	0.992112	1.256713	0.888606	1.232495	1.497343
	[28.6903]**	[47.8893]**	[27.3246]**	[34.5308]**	[24.4403]**	[24.0960]**

Eq Name:	Period 4					
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.380001	-0.191621	0.549148	0.145643	0.775089	0.005107
	[2.8291]**	[-2.1682]*	[3.1000]**	[1.7292]	[3.6269]**	[0.0258]
MKT_RF	0.862635	1.060837	1.025579	0.921020	0.989907	1.273659
	[18.8554]**	[38.6030]**	[15.2078]**	[34.5036]**	[12.1244]**	[23.2301]**

Eq Name:	Period 5					
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.222373	-0.005109	0.434295	0.233412	0.640126	-0.369411
	[1.1185]	[-0.0692]	[2.0026]*	[1.4145]	[2.6930]**	[-1.2392]

MKT_RF	0.855967	1.035701	0.901025	0.778696	0.865163	1.372320
	[14.9016]**	[50.0004]**	[14.3927]**	[14.5367]**	[12.3495]**	[19.7622]**

Eq Name:	**Period 6**					
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	-0.176393	0.136881	0.066095	-0.083686	-0.035945	-0.147851
	[-0.8460]	[1.8196]	[0.3689]	[-1.1582]	[-0.1528]	[-0.6736]
MKT_RF	1.229180	0.888238	1.197742	1.020737	1.286532	1.239888
	[25.8699]**	[51.8162]**	[29.3326]**	[61.9929]**	[23.9973]**	[24.7890]**

9.10.2 Indian Portfolios

Eq Name:	**Period 1**					
Dep. Var:	PORTFOLIO1-RF__	_2_PORTFOLIO-RF__	_3_PORTFOLIO-RF__	_4_PORTFOLIO-RF__	_5_PORTFOLIO-RF__	_6_PORTFOLIO-RF__
C	0.008113	0.012082	-0.062968	0.008656	-0.076153	-0.034040
	[0.1497]	[1.3829]	[-2.7746]**	[0.3872]	[-2.7059]**	[-1.7442]
RM_RF__	1.312451	0.964600	0.765777	1.241342	0.782367	0.771576
	[24.8693]**	[91.0389]**	[30.9759]**	[53.3031]**	[23.4049]**	[37.1764]**

Eq Name:	**Period 2**					
Dep. Var:	PORTFOLIO1-RF__	_2_PORTFOLIO-RF__	_3_PORTFOLIO-RF__	_4_PORTFOLIO-RF__	_5_PORTFOLIO-RF__	_6_PORTFOLIO-RF__
C	0.032456	-0.001067	0.073586	0.075539	0.109355	0.012925
	[0.3985]	[-0.2864]	[3.0980]**	[2.3293]*	[3.3339]**	[0.6384]
RM_RF__	0.957022	0.945347	0.767625	0.982330	0.825032	0.781372
	[15.2578]**	[177.4908]**	[40.5798]**	[32.2587]**	[33.8059]**	[56.1879]**

Eq Name:	**Period 3**					
Dep. Var:	PORTFOLIO 1-RF__	_2_PORTFO LIO-RF__	_3_PORTFO LIO-RF__	_4_PORTFO LIO-RF__	_5_PORTFO LIO-RF__	_6_PORTFO LIO-RF__
C	0.422449	-0.002539	0.020231	0.006275	0.074773	0.016009
	[9.5402]**	[-0.5049]	[0.9647]	[0.3736]	[2.6846]**	[0.8588]
RM_RF__	0.902390	0.995313	0.867801	1.097032	0.828798	0.791007
	[22.7046]**	[191.3963]**	[31.8486]**	[84.0223]**	[23.6730]**	[31.6886]**

Eq Name:	**Period 4**					
Dep. Var:	_1_PORTFOL IO-RF__	_2_PORTFOL IO-RF__	_3_PORTFOL IO-RF__	_4_PORTFOL IO-RF__	_5_PORTFOL IO-RF__	_6_PORT FOLIO- RF__
C	-0.076575	-0.001067	0.022823	-0.012745	0.009245	0.018435
	[-1.9867]*	[-0.2600]	[1.1583]	[-0.7580]	[0.3530]	[1.2996]
RM_RF__	1.719449	0.945347	1.123010	1.279355	1.188694	0.836766
	[39.6886]**	[139.5737]**	[30.6000]**	[47.0119]**	[27.0027]**	[30.0847]**
R-squared:	0.5532	0.9762	0.7475	0.8283	0.6607	0.7565

9.11 Results of First-Step Regression

9.11.1 USA CAPM 6 and 25 Portfolios

Eq Name:	CAPM1	CAPM2	CAPM3
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF
C	0.127693	-0.0059	0.212867
	[1.3985]	[-0.1736]	[2.3826]*
MKT_RF	1.214517	0.968645	1.186968
	[71.9132]**	[154.1610]**	[71.8293]**
R-squared:	0.8267	0.9564	0.8264
Eq Name:	**CAPM4**	**CAPM5**	**CAPM6**
Dep. Var:	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.030054	0.333683	-0.13129
	[0.5738]	[2.6914]**	[-1.2558]
MKT_RF	1.011039	1.324404	1.255726
	[104.3554]**	[57.7536]**	[64.9371]**
R-squared:	0.9095	0.7547	0.7955

Eq Name:	CAPM1	CAPM2	CAPM3	CAPM4	CAPM5
Dep. Var:	BIG_HIBM-RF	BIG_LOBM-RF	ME1_BM2-RF	ME1_BM3-RF	ME1_BM4-RF
C	0.107192	-0.01145	-0.22484	0.100034	0.361446
	[0.7520]	[-0.2479]	[-1.3471]	[0.6920]	[2.8246]**
MKT_RF	1.311968	0.955298	1.409005	1.372905	1.269597
	[17.8111]**	[65.8934]**	[14.4909]**	[19.3141]**	[17.3147]**
R-squared:	0.675	0.9179	0.5876	0.6676	0.6641
Eq Name:	**CAPM6**	**CAPM7**	**CAPM8**	**CAPM9**	**CAPM10**
Dep. Var:	ME2_BM1-RF	ME2_BM2-RF	ME2_BM3-RF	ME2_BM4-RF	ME2_BM5-RF
C	-0.20809	0.126117	0.210932	0.292097	0.359031
	[-1.7237]	[1.2638]	[2.2914]*	[2.9798]**	[2.7736]**
MKT_RF	1.26566	1.226319	1.197724	1.212608	1.378677
	[23.8920]**	[23.7158]**	[25.3574]**	[23.3885]**	[21.3306]**
R-squared:	0.72	0.7676	0.7814	0.7655	0.7205
Eq Name:	**CAPM11**	**CAPM12**	**CAPM13**	**CAPM14**	**CAPM15**
Dep. Var:	ME3_BM1-RF	ME3_BM2-RF	ME3_BM3-RF	ME3_BM4-RF	ME3_BM5-RF

C	-0.11381	0.17315	0.201541	0.263251	0.259592
	[-1.2419]	[2.4737]*	[2.7870]**	[3.1617]**	[2.1828]*
MKT_RF	1.245059	1.125546	1.123793	1.159576	1.377846
	[35.0389]**	[53.7083]**	[35.4048]**	[24.7883]**	[24.7630]**
R-squared:	0.8104	0.869	0.8545	0.8119	0.7525
Eq Name:	**CAPM16**	**CAPM17**	**CAPM18**	**CAPM19**	**CAPM20**
Dep. Var:	ME4_BM1-RF	ME4_BM2-RF	ME4_BM3-RF	ME4_BM4-RF	ME4_BM5-RF
C	-0.00225	0.043403	0.135171	0.217835	0.107926
	[-0.0333]	[0.7616]	[1.9928]*	[2.6836]**	[0.8886]
MKT_RF	1.091849	1.079583	1.115235	1.154073	1.42037
	[47.7349]**	[49.5904]**	[30.4931]**	[24.9408]**	[21.0089]**
R-squared:	0.8738	0.9056	0.8671	0.826	0.7622
Eq Name:	**CAPM21**	**CAPM22**	**CAPM23**	**CAPM24**	**CAPM25**
Dep. Var:	ME5_BM2-RF	ME5_BM3-RF	ME5_BM4-RF	SMALL_HIBM-RF	SMALL_LOBM-RF
C	0.00742	0.071087	-0.06826	0.467645	-0.49875
	[0.1645]	[1.0655]	[-0.7656]	[3.1641]**	[-2.2334]*
MKT_RF	0.949813	0.968355	1.108542	1.379884	1.630229
	[73.7402]**	[31.6949]**	[26.6748]**	[15.7310]**	[11.4010]**
R-squared:	0.9211	0.8462	0.8073	0.6325	0.5097

9.11.2 USA CAPM FF 6 and 25 Portfolios

Eq Name:	**FF1**	**FF2**	**FF3**
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF
C	-0.11163	0.070409	0.052558
	[-2.8751]**	[3.1370]**	[1.6447]
MKT_RF	1.085997	1.022018	0.984285
	[140.5390]**	[228.7873]**	[154.7585]**
SMB	0.018613	-0.09158	0.818022
	[1.4739]	[-12.5439]**	[78.7016]**
HML	0.79464	-0.22818	0.29539
	[70.2780]**	[-34.9088]**	[31.7402]**
R-squared:	0.969	0.9811	0.978

Eq Name:	FF4	FF5	FF6
Dep. Var:	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	-0.05508	0.016526	-0.16584
	[-1.4269]	[0.7421]	[-4.5032]**
MKT_RF	0.986331	1.023025	1.086994
	[128.3914]**	[230.8059]**	[148.2999]**
SMB	-0.13853	0.930168	1.040279
	[-11.0345]**	[128.4125]**	[86.8458]**
HML	0.325356	0.786795	-0.19042
	[28.9436]**	[121.3116]**	[-17.7542]**
R-squared:	0.9513	0.9922	0.9749

Eq Name:	CAPM1B	CAPM2B	CAPM3B	CAPM4B	CAPM5B
Dep. Var:	BIG_HIBM-RF	BIG_LOBM-RF	ME1_BM2-RF	ME1_BM3-RF	ME1_BM4-RF
C	-0.18424	0.080119	-0.42757	-0.16347	0.082086
	[-1.7509]	[2.3213]*	[-3.6818]**	[-1.9282]	[1.2904]
MKT_RF	1.18052	1.024581	1.080602	1.054724	0.945647
	[30.5486]**	[110.5331]**	[25.9253]**	[28.4039]**	[42.9830]**
SMB	-0.15045	-0.14607	1.532568	1.241161	1.22341
	[-2.1319]*	[-6.2104]**	[10.2357]**	[25.0639]**	[13.5038]**
HML	1.01858	-0.26317	0.227055	0.515954	0.574192
	[13.7374]**	[-16.2017]**	[2.2015]*	[10.4027]**	[11.5997]**
R-squared:	0.8389	0.9541	0.8209	0.8887	0.9269
Eq Name:	**CAPM6B**	**CAPM7B**	**CAPM8B**	**CAPM9B**	**CAPM10B**
Dep. Var:	ME2_BM1-RF	ME2_BM2-RF	ME2_BM3-RF	ME2_BM4-RF	ME2_BM5-RF
C	-0.23984	-0.0004	0.033184	0.051824	0.014053
	[-3.3552]**	[-0.0069]	[0.6414]	[1.1309]	[0.2545]
MKT_RF	1.086415	1.018416	0.98367	0.969082	1.065138
	[36.0069]**	[52.2270]**	[45.6186]**	[53.1093]**	[62.7976]**
SMB	1.123092	0.97685	0.833241	0.809744	0.913123
	[17.6427]**	[15.1445]**	[12.8714]**	[12.2285]**	[17.1323]**
HML	-0.22414	0.135702	0.349219	0.565164	0.884821
	[-3.8905]**	[3.1887]**	[10.0491]**	[15.7953]**	[24.4522]**
R-squared:	0.9074	0.9303	0.9351	0.9502	0.9518
Eq Name:	**CAPM11B**	**CAPM12B**	**CAPM13B**	**CAPM14B**	**CAPM15B**
Dep. Var:	ME3_BM1-RF	ME3_BM2-RF	ME3_BM3-RF	ME3_BM4-RF	ME3_BM5-RF
C	-0.11694	0.11544	0.069556	0.057808	-0.05477
	[-2.1181]*	[2.2022]*	[1.3233]	[1.0947]	[-0.8337]
MKT_RF	1.125195	1.021629	0.990647	0.984266	1.127416
	[68.3251]**	[66.2577]**	[42.3415]**	[65.4363]**	[66.6969]**

SMB	0.816762	0.508335	0.440476	0.464954	0.588302
	[19.8794]**	[16.4623]**	[12.8873]**	[10.2667]**	[9.0101]**
HML	-0.22972	0.043447	0.311725	0.550115	0.877989
	[-5.9421]**	[1.4691]	[9.7526]**	[15.5494]**	[17.8658]**
R-squared:	0.9301	0.927	0.9263	0.9325	0.9262
Eq Name:	**CAPM16B**	**CAPM17B**	**CAPM18B**	**CAPM19B**	**CAPM20B**
Dep. Var:	ME4_BM1-RF	ME4_BM2-RF	ME4_BM3-RF	ME4_BM4-RF	ME4_BM5-RF
C	0.075091	-0.00247	0.012984	0.029805	-0.19919
	[1.5435]	[-0.0483]	[0.2313]	[0.5088]	[-2.5205]*
MKT_RF	1.084992	1.021622	1.021482	1.026899	1.216762
	[71.6175]**	[50.7526]**	[49.9544]**	[46.8021]**	[54.7318]**
SMB	0.328327	0.233825	0.203897	0.195624	0.291127
	[8.5676]**	[7.2113]**	[5.7904]**	[6.3822]**	[6.4103]**
HML	-0.35513	0.084597	0.348543	0.571107	0.941158
	[-11.6712]**	[2.9202]**	[8.0326]**	[12.9393]**	[23.3660]**
R-squared:	0.9333	0.922	0.9121	0.9172	0.9103
Eq Name:	**CAPM21B**	**CAPM22B**	**CAPM23B**	**CAPM24B**	**CAPM25B**
Dep. Var:	ME5_BM2-RF	ME5_BM3-RF	ME5_BM4-RF	SMALL_HIBM-RF	SMALL_LOBM-RF
C	0.020023	-0.00794	-0.24594	0.079823	-0.75374
	[0.4680]	[-0.1450]	[-4.2813]**	[1.2678]	[-4.2423]**
MKT_RF	0.985532	0.963267	1.042132	0.987187	1.288318
	[76.8069]**	[53.9321]**	[48.1678]**	[40.4366]**	[10.7160]**
SMB	-0.201	-0.25191	-0.18658	1.3044	1.436006
	[-10.5097]**	[-9.2482]**	[-6.1611]**	[19.7804]**	[8.0691]**
HML	0.016976	0.338282	0.648883	0.912993	0.43022
	[0.8696]	[12.9351]**	[23.6178]**	[15.3377]**	[1.5541]
R-squared:	0.9343	0.9034	0.9228	0.939	0.6551

9.11.3 Downside Beta 6 and 25 Portfolios

Eq Name:	**DOWNSIDECAPM1**	**DOWNSIDECAPM2**	**DOWNSIDECAPM3**
Dep. Var:	YT1	YT2	YT3
XT	1.118055	0.974451	1.14713
	[30.4824]**	[85.8001]**	[45.7977]**
R-squared:	0.775	0.9478	0.84
Eq Name:	**DOWNSIDECAPM4**	**DOWNSIDECAPM5**	**DOWNSIDECAPM6**
Dep. Var:	YT4	YT5	YT6

XT	0.954467	1.230547	1.249287
	[44.1210]**	[36.1925]**	[41.5238]**
R-squared:	0.8833	0.772	0.8214

Eq Name :	DOWNSIDECAPM1	DOWNSIDECAPM2	DOWNSIDECAPM3	DOWNSIDECAPM4	DOWNSIDECAPM5
Dep. Var:	YT1	YT2	YT3	YT4	YT5
XT	1.212206	0.960113	1.339097	1.251126	1.184799
	[20.1859]**	[63.4827]**	[28.5283]**	[26.2225]**	[31.9820]**
R-squared:	0.6096	0.8999	0.6311	0.6764	0.7177
Eq Name :	**DOWNSIDECAPM6**	**DOWNSIDECAPM7**	**DOWNSIDECAPM8**	**DOWNSIDECAPM9**	**DOWNSIDECAPM10**
Dep. Var:	YT6	YT7	YT8	YT9	YT10
XT	1.276417	1.091355	1.078771	1.221731	1.216828
	[31.5937]**	[39.6170]**	[35.8580]**	[30.9115]**	[47.4205]**
R-squared:	0.7417	0.8033	0.7758	0.7177	0.8373
Eq Name :	**DOWNSIDECAPM11**	**DOWNSIDECAPM12**	**DOWNSIDECAPM13**	**DOWNSIDECAPM14**	**DOWNSIDECAPM15**
Dep. Var:	YT11	YT12	YT13	YT14	YT15
XT	1.097658	1.039407	1.030512	1.199335	1.108629
	[50.4673]**	[38.6484]**	[35.4013]**	[31.5938]**	[49.5251]**
R-squared:	0.8611	0.8355	0.7893	0.7312	0.8815
Eq Name :	**DOWNSIDECAPM16**	**DOWNSIDECAPM17**	**DOWNSIDECAPM18**	**DOWNSIDECAPM19**	**DOWNSIDECAPM20**
Dep. Var:	YT16	YT17	YT18	YT19	YT20
XT	1.041083	1.028643	1.023845	1.024685	1.024032
	[47.1451]**	[40.6384]**	[39.7826]**	[40.3500]**	[40.0372]**
R-squared:	0.8876	0.8404	0.8166	0.8147	0.8058
Eq Name :	**DOWNSIDECAPM21**	**DOWNSIDECAPM22**	**DOWNSIDECAPM23**	**DOWNSIDECAPM24**	**DOWNSIDECAPM25**

Dep. Var:	YT21	YT22	YT23	YT24	YT25
XT	1.020304	1.023432	1.016223	1.0119	1.020411
	[39.9624]**	[40.0598]**	[39.1707]**	[38.9400]**	[39.7724]**
R-squared:	0.7918	0.8044	0.7779	0.746	0.8053

9.11.4 US Downside Beta FF 6 and 25 Portfolios

Eq Name:	**DOWNSIDECAPM11**	**DOWNSIDECAPM21**	**DOWNSIDECAPM31**
Dep. Var:	YT1	YT2	YT3
XT	1.130022	0.979254	1.112461
	[43.2907]**	[94.0022]**	[52.3259]**
SMB	-0.09045	-0.026	0.208869
	[-3.6480]**	[-2.3435]*	[5.4415]**
HML	0.316207	-0.06996	0.100028
	[6.7487]**	[-5.5359]**	[3.4923]**
R-squared:	0.8446	0.9542	0.8752
Eq Name:	**DOWNSIDECAPM41**	**DOWNSIDECAPM51**	**DOWNSIDECAPM61**
Dep. Var:	YT4	YT5	YT6
XT	0.966967	1.194084	1.198264
	[52.2239]**	[44.7000]**	[51.2819]**
SMB	-0.08456	0.212795	0.3213
	[-4.8160]**	[4.3081]**	[7.1799]**
HML	0.14064	0.236679	-0.11842
	[6.0727]**	[5.1920]**	[-4.3166]**
R-squared:	0.9069	0.8315	0.8753

Eq Name:	**DOWNSIDECAPM1B**	**DOWNSIDECAPM2B**	**DOWNSIDECAPM3B**	**DOWNSIDECAPM4B**	**DOWNSIDECAPM5B**
Dep. Var:	YT1	YT2	YT3	YT4	YT5
XT	1.23136	0.970089	1.280358	1.198462	1.140388
	[23.9741]**	[69.3706]**	[28.5465]**	[27.5935]**	[34.3515]**

SMB	-0.13889	-0.05712	0.361749	0.318627	0.266216
	[-3.6825]**	[-3.4098]**	[5.5900]**	[5.4240]**	[5.1152]**
HML	0.393463	-0.08565	0.019062	0.126251	0.15376
	[6.2610]**	[-5.2271]**	[0.4372]	[3.0465]**	[3.7993]**
R-squared:	0.6866	0.9118	0.6785	0.7323	0.7712
Eq Name:	**DOWNSIDECAPM6B**	**DOWNSIDECAPM7B**	**DOWNSIDECAPM8B**	**DOWNSIDECAPM9B**	**DOWNSIDECAPM10B**
Dep. Var:	YT6	YT7	YT8	YT9	YT10
XT	1.221386	1.057581	1.048435	1.186844	1.179155
	[35.7508]**	[43.4491]**	[42.7062]**	[37.4439]**	[54.6198]**
SMB	0.347358	0.203133	0.178178	0.201294	0.2399
	[6.9849]**	[5.2563]**	[4.4111]**	[3.9190]**	[6.5998]**
HML	-0.14346	0.103868	0.175214	0.270465	-0.13839
	[-4.2397]**	[3.4838]**	[4.8193]**	[5.2561]**	[-5.2015]**
R-squared:	0.8	0.8391	0.8221	0.7807	0.8745
Eq Name:	**DOWNSIDECAPM11B**	**DOWNSIDECAPM12B**	**DOWNSIDECAPM13B**	**DOWNSIDECAPM14B**	**DOWNSIDECAPM15B**
Dep. Var:	YT11	YT12	YT13	YT14	YT15
XT	1.072469	1.018308	1.013626	1.179542	1.089765
	[54.6213]**	[41.6658]**	[41.8308]**	[38.4769]**	[57.9444]**
SMB	0.15376	0.124521	0.094299	0.107082	0.123559
	[5.5087]**	[4.3705]**	[3.0251]**	[2.5467]*	[6.8592]**
HML	0.034331	0.11034	0.190679	0.289432	-0.13496
	[1.6553]	[4.2887]**	[5.3672]**	[5.7833]**	[-6.1661]**
R-squared:	0.8776	0.8588	0.8277	0.7872	0.9027
Eq Name:	**DOWNSIDECAPM16B**	**DOWNSIDECAPM17B**	**DOWNSIDECAPM18B**	**DOWNSIDECAPM19B**	**DOWNSIDECAPM20B**

Dep. Var:	YT16	YT17	YT18	YT19	YT20
XT	1.026707	1.02172	1.01509	1.01581	1.010558
	[49.0424]**	[44.9906]**	[44.1659]**	[44.3424]**	[44.9632]**
SMB	0.08682	0.03587	0.047225	0.048437	0.075075
	[4.6126]**	[1.7319]	[2.1056]*	[2.1479]*	[2.6945]**
HML	0.037506	0.131475	0.130755	0.121729	0.155363
	[2.0535]*	[4.8269]**	[4.6330]**	[4.4346]**	[4.9636]**
R-squared:	0.8948	0.857	0.833	0.829	0.83
Eq Name:	**DOWNSIDECAPM21B**	**DOWNSIDECAPM22B**	**DOWNSIDECAPM23B**	**DOWNSIDECAPM24B**	**DOWNSIDECAPM25B**
Dep. Var:	YT21	YT22	YT23	YT24	YT25
XT	1.002908	1.005241	1.016055	1.010147	1.018507
	[44.1202]**	[43.5995]**	[43.0474]**	[43.8193]**	[44.4233]**
SMB	0.100232	0.106102	-0.00649	0.000924	0.003333
	[3.3422]**	[3.5069]**	[-0.2168]	[0.0284]	[0.1133]
HML	0.137548	0.119197	0.14383	0.18915	0.160905
	[4.5449]**	[4.0857]**	[4.7851]**	[5.4096]**	[5.2003]**
R-squared:	0.8146	0.8246	0.7933	0.7709	0.8258

9.11.5 Asia Pacific CAPM

Eq Name:	**CAPM1**	**CAPM2**	**CAPM3**
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF
C	0.215307	-0.08112	-0.14886
	[1.5603]	[-0.8737]	[-1.0099]
MKT_RF	1.117833	0.973047	1.015277
	[27.1897]**	[41.8873]**	[33.0897]**
R-squared:	0.8652	0.9257	0.8448
Eq Name:	**CAPM4**	**CAPM5**	**CAPM6**
Dep. Var:	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.013378	0.27863	-0.62673

	[0.2143]	[1.4535]	[-3.5776]**
MKT_RF	0.969941	1.003495	1.031355
	[79.1650]**	[22.8233]**	[24.9657]**
R-squared:	0.9657	0.7529	0.7954

Eq Name:	**CAPM1**	**CAPM2**	**CAPM3**	**CAPM4**	**CAPM5**
Dep. Var:	BIG_HIBM-RF	BIG_LOBM-RF	ME1_BM2-RF	ME1_BM3-RF	ME1_BM4-RF
C	0.164663	-0.13139	-0.37149	0.01021	0.399416
	[0.7811]	[-0.9633]	[-1.5190]	[0.0456]	[1.7567]
MKT_RF	1.162853	0.978918	1.056995	1.009632	0.975473
	[21.1787]**	[31.1221]**	[23.6501]**	[23.6743]**	[23.8014]**
R-squared:	***0.7587***	***0.8535***	***0.6843***	***0.7027***	***0.6807***
Eq Name:	**CAPM6**	**CAPM7**	**CAPM8**	**CAPM9**	**CAPM10**
Dep. Var:	ME2_BM1-RF	ME2_BM2-RF	ME2_BM3-RF	ME2_BM4-RF	ME2_BM5-RF
C	-0.78081	-0.54335	-0.32658	-0.12441	0.166975
	[-3.8254]**	[-2.9122]**	[-1.8875]	[-0.6837]	[0.7145]
MKT_RF	0.996984	1.093498	0.973744	1.004875	1.04361
	[23.6210]**	[25.2254]**	[27.9197]**	[27.6414]**	[18.4647]**
R-squared:	***0.7303***	***0.7894***	***0.7787***	***0.7759***	***0.6902***
Eq Name:	**CAPM11**	**CAPM12**	**CAPM13**	**CAPM14**	**CAPM15**
Dep. Var:	ME3_BM1-RF	ME3_BM2-RF	ME3_BM3-RF	ME3_BM4-RF	ME3_BM5-RF
C	-0.59675	-0.42607	0.020291	0.013565	0.012011
	[-2.9347]**	[-2.3487]*	[0.1201]	[0.0847]	[0.0567]
MKT_RF	1.029347	1.01273	1.01488	1.010946	1.07153
	[24.1715]**	[20.6495]**	[26.1364]**	[30.1984]**	[21.3130]**
R-squared:	***0.7378***	***0.7864***	***0.8031***	***0.8106***	***0.7429***
Eq Name:	**CAPM16**	**CAPM17**	**CAPM18**	**CAPM19**	**CAPM20**
Dep. Var:	ME4_BM1-RF	ME4_BM2-RF	ME4_BM3-RF	ME4_BM4-RF	ME4_BM5-RF
C	-0.12849	0.137752	-0.12386	0.091957	0.177272
	[-0.7891]	[0.9111]	[-0.8951]	[0.6442]	[0.9992]
MKT_RF	0.972416	0.932839	0.961416	1.005691	1.171519
	[21.2750]**	[24.5302]**	[30.0354]**	[33.6615]**	[23.0721]**
R-squared:	***0.8054***	***0.8167***	***0.8404***	***0.8516***	***0.8112***
Eq Name:	**CAPM25**	**CAPM21**	**CAPM22**	**CAPM23**	**CAPM24**
Dep. Var:	SMALL_LOBM-RF	ME5_BM2-RF	ME5_BM3-RF	ME5_BM4-RF	SMALL_HIBM-RF
C	-0.24558	0.042302	0.11362	0.047984	0.794813

	[-0.7950]	[0.4470]	[1.0478]	[0.3603]	[3.1371]**
MKT_RF	1.034861	0.982151	0.995353	0.983089	0.936698
	[20.5130]**	[50.4567]**	[44.0206]**	[38.9732]**	[19.8294]**
R-squared:	**0.5561**	***0.9204***	***0.9072***	***0.8597***	***0.6094***

9.11.6 Asia Pacific CAPM FF

Eq Name:	**CAPM11**	**CAPM21**	**CAPM31**
Dep. Var:	_1_PORTFOLIO-RF	_2_PORTFOLIO-RF	_3_PORTFOLIO-RF
C	-0.25566	0.140358	0.014618
	[-3.2756]**	[2.1435]*	[0.2690]
MKT_RF	1.074926	0.996261	1.017217
	[74.9432]**	[75.9253]**	[106.1701]**
SMB	-0.17026	-0.09502	0.805966
	[-5.0541]**	[-4.3908]**	[39.3747]**
HML	0.723092	-0.40263	0.015961
	[15.3610]**	[-15.2446]**	[0.7152]
R-squared:	0.9639	0.967	0.9801
Eq Name:	**CAPM41**	**CAPM51**	**CAPM61**
Dep. Var:	_4_PORTFOLIO-RF	_5_PORTFOLIO-RF	_6_PORTFOLIO-RF
C	0.005663	0.135821	-0.26045
	[0.0876]	[2.6254]**	[-3.7117]**
MKT_RF	0.970418	0.972823	1.05156
	[80.4142]**	[113.2961]**	[76.7802]**
SMB	-0.07078	0.96672	0.891399
	[-3.4244]**	[54.6420]**	[25.8518]**
HML	-0.01246	0.583259	-0.29107
	[-0.5405]	[30.1662]**	[-6.7531]**
R-squared:	0.967	0.9843	0.9675

Eq Name:	**CAPM1B**	**CAPM2B**	**CAPM3B**	**CAPM4B**	**CAPM5B**
Dep. Var:	BIG_HIBM-RF	BIG_LOBM-RF	ME1_BM2-RF	ME1_BM3-RF	ME1_BM4-RF
C	-0.42797	0.118386	-0.03615	0.235869	0.533662
	[-2.7801]**	[1.0711]	[-0.2405]	[1.8863]	[4.3884]**
MKT_RF	1.11066	1.006056	1.07031	1.012731	0.969001
	[38.6754]**	[48.7162]**	[48.4264]**	[46.3349]**	[49.0637]**
SMB	-0.31793	-0.16244	1.114968	1.088248	1.126866
	[-4.8441]**	[-3.8728]**	[17.3378]**	[17.7454]**	[25.2556]**
HML	0.872835	-0.47383	-0.15966	0.013362	0.179327
	[16.1153]**	[-9.4679]**	[-2.7702]**	[0.3128]	[4.3715]**

R-squared:	***0.8851***	***0.9083***	***0.8848***	***0.9102***	***0.914***
Eq Name:	**CAPM6B**	**CAPM7B**	**CAPM8B**	**CAPM9B**	**CAPM10B**
Dep. Var:	ME2_BM1-RF	ME2_BM2-RF	ME2_BM3-RF	ME2_BM4-RF	ME2_BM5-RF
C	-0.4711	-0.28147	-0.13319	-0.11583	-0.0967
	[-3.0756]**	[-2.2976]*	[-1.0878]	[-1.0214]	[-0.8035]
MKT_RF	1.013326	1.104526	0.979359	0.991638	1.001179
	[42.0594]**	[48.0972]**	[51.9827]**	[55.3491]**	[45.5046]**
SMB	0.796553	0.834428	0.762	0.811336	0.96614
	[9.9586]**	[15.8255]**	[15.9678]**	[17.7153]**	[23.0048]**
HML	-0.23081	-0.13766	-0.04954	0.275737	0.784238
	[-3.9425]**	[-2.8568]**	[-1.3618]	[6.4095]**	[21.6600]**
R-squared:	***0.8623***	***0.9115***	***0.9013***	***0.9151***	***0.9271***
Eq Name:	**CAPM11B**	**CAPM12B**	**CAPM13B**	**CAPM14B**	**CAPM15B**
Dep. Var:	ME3_BM1-RF	ME3_BM2-RF	ME3_BM3-RF	ME3_BM4-RF	ME3_BM5-RF
C	-0.2181	-0.19097	0.193897	0.008774	-0.28984
	[-1.3076]	[-1.2954]	[1.3311]	[0.0641]	[-1.9276]
MKT_RF	1.055534	1.026063	1.02158	1.001386	1.031513
	[38.7212]**	[28.9107]**	[32.3563]**	[37.9023]**	[34.3756]**
SMB	0.615968	0.551132	0.588373	0.524306	0.612667
	[10.2898]**	[8.3672]**	[10.1761]**	[9.9153]**	[9.4963]**
HML	-0.41012	-0.19434	-0.07867	0.195383	0.721435
	[-6.6955]**	[-3.0389]**	[-1.1268]	[4.0607]**	[10.9505]**
R-squared:	***0.839***	***0.8551***	***0.874***	***0.8717***	***0.8825***
Eq Name:	**CAPM16B**	**CAPM17B**	**CAPM18B**	**CAPM19B**	**CAPM20B**
Dep. Var:	ME4_BM1-RF	ME4_BM2-RF	ME4_BM3-RF	ME4_BM4-RF	ME4_BM5-RF
C	0.099935	0.268501	0.001458	0.068418	-0.21452
	[0.7031]	[1.7859]	[0.0107]	[0.4953]	[-1.6473]
MKT_RF	0.988013	0.942532	0.969408	0.999139	1.129155
	[28.7841]**	[28.1513]**	[34.5631]**	[36.3447]**	[36.6671]**
SMB	0.383142	0.175184	0.242762	0.245637	0.243006
	[5.8782]**	[3.2373]**	[4.1339]**	[4.9159]**	[4.2296]**
HML	-0.24328	-0.15502	-0.12183	0.126982	0.739016
	[-4.4597]**	[-2.4787]*	[-2.0748]*	[2.1432]*	[12.0125]**

R-squared:	***0.852***	***0.8304***	***0.8581***	***0.8673***	***0.8989***
Eq Name:	**CAPM21B**	**CAPM22B**	**CAPM23B**	**CAPM24B**	**CAPM25B**
Dep. Var:	ME5_BM2-RF	ME5_BM3-RF	ME5_BM4-RF	SMALL_HIBM-RF	SMALL_LOBM-RF
C	0.121072	0.082747	-0.23753	0.748101	0.201923
	[1.4354]	[0.7343]	[-2.1745]*	[6.3701]**	[0.8838]
MKT_RF	0.992905	0.993752	0.959438	0.910506	1.056159
	[58.5356]**	[45.8316]**	[48.3674]**	[45.8447]**	[30.5021]**
SMB	-0.17785	-0.08101	-0.23924	1.247912	1.284415
	[-5.9529]**	[-1.8378]	[-5.6874]**	[21.5141]**	[11.6623]**
HML	-0.19469	0.022434	0.38974	0.523809	-0.28578
	[-5.4701]**	[0.5578]	[9.1361]**	[12.9052]**	[-3.0316]**
R-squared:	***0.9364***	***0.9089***	***0.9089***	***0.9214***	***0.7897***

9.11.7 Asia Pacific Downside Beta 6 and 25 Portfolios

Eq Name:	**DOWNSIDECAPM1**	**DOWNSIDECAPM2**	**DOWNSIDECAPM3**
Dep. Var:	YT1	YT2	YT3
XT	1.045324	0.993383	1.048083
	[39.4254]**	[32.4827]**	[26.5738]**
R-squared:	***0.8566***	***0.9101***	***0.8405***
Eq Name:	**DOWNSIDECAPM4**	**DOWNSIDECAPM5**	**DOWNSIDECAPM6**
Dep. Var:	YT4	YT5	YT6
XT	0.964842	1.029111	1.104924
	[55.6221]**	[23.1375]**	[24.8273]**
R-squared:	***0.955***	***0.7739***	***0.8306***

Eq Name:	**DOWNSIDECAPM1**	**DOWNSIDECAPM2**	**DOWNSIDECAPM3**	**DOWNSIDECAPM4**	**DOWNSIDECAPM5**
Dep. Var:	YT1	YT2	YT3	YT4	YT5
XT	1.085061	1.011376	1.142891	1.071028	1.032301
	[23.5077]**	[26.0688]**	[21.0785]**	[20.7474]**	[21.3672]**
R-squared:	0.7265	0.845	0.6962	0.7128	0.7104

Eq Name :	**DOWNSIDECAPM6**	**DOWNSIDECAPM7**	**DOWNSIDECAPM8**	**DOWNSIDECAPM9**	**DOWNSIDECAPM10**
Dep. Var:	YT6	YT7	YT8	YT9	YT10
XT	1.084701	0.97172	0.968861	0.988093	1.078051
	[25.7259]**	[23.6102]**	[21.2165]**	[16.4232]**	[24.1043]**
R-squared:	0.7842	0.7887	0.7671	0.7131	0.7779
Eq Name :	**DOWNSIDECAPM11**	**DOWNSIDECAPM12**	**DOWNSIDECAPM13**	**DOWNSIDECAPM14**	**DOWNSIDECAPM15**
Dep. Var:	YT11	YT12	YT13	YT14	YT15
XT	1.042139	0.963838	0.914846	1.001677	0.972919
	[15.4246]**	[16.9111]**	[23.1662]**	[18.1720]**	[15.6436]**
R-squared:	0.7974	0.8108	0.7993	0.7524	0.8179
Eq Name :	**DOWNSIDECAPM16**	**DOWNSIDECAPM17**	**DOWNSIDECAPM18**	**DOWNSIDECAPM19**	**DOWNSIDECAPM20**
Dep. Var:	YT16	YT17	YT18	YT19	YT20
XT	0.885349	0.923644	0.917307	0.911716	0.908412
	[16.5177]**	[21.8912]**	[21.4493]**	[20.9536]**	[20.5337]**
R-squared:	0.7957	0.863	0.8355	0.8053	0.8163
Eq Name :	**DOWNSIDECAPM21**	**DOWNSIDECAPM22**	**DOWNSIDECAPM23**	**DOWNSIDECAPM24**	**DOWNSIDECAPM25**
Dep. Var:	YT21	YT22	YT23	YT24	YT25
XT	0.902823	0.898159	0.872102	0.871145	0.903575
	[20.1017]**	[19.9502]**	[17.3962]**	[17.7123]**	[20.3211]**
R-squared:	0.7971	0.7972	0.7776	0.7493	0.8067

9.11.8 Downside Beta FF 6 and 25 Portfolios

Eq Name:	DOWNSIDECAPM11	DOWNSIDECAPM21	DOWNSIDECAPM31
Dep. Var:	YT1	YT2	YT3
XT	1.071237	0.984619	1.023389
	[52.0020]**	[37.4962]**	[41.3480]**
SMB	-0.09827	-0.08039	0.381571
	[-2.6335]**	[-3.3195]**	[8.2405]**
HML	0.218116	-0.1629	0.018017
	[3.8328]**	[-4.4291]**	[0.6637]
R-squared:	0.8878	0.9288	0.9101
Eq Name:	**DOWNSIDECAPM41**	**DOWNSIDECAPM51**	**DOWNSIDECAPM61**
Dep. Var:	YT4	YT5	YT6
XT	0.96816	1.01845	1.070089
	[55.8480]**	[38.6909]**	[36.6531]**
SMB	-0.0297	0.426522	0.400068
	[-1.7656]	[7.9025]**	[8.2603]**
HML	0.014491	0.213145	-0.083
	[1.0036]	[4.6513]**	[-1.8781]
R-squared:	0.9558	0.8753	0.9038

Eq Name:	DOWNSIDECAPM1B	DOWNSIDECAPM2B	DOWNSIDECAPM3B	DOWNSIDECAPM4B	DOWNSIDECAPM5B
Dep. Var:	YT1	YT2	YT3	YT4	YT5
XT	1.120197	1.001873	1.100075	1.036516	1.00181
	[27.1988]**	[31.5915]**	[31.1115]**	[30.4503]**	[32.3735]**
SMB	-0.16214	-0.12571	0.570264	0.519152	0.518386
	[-2.9488]**	[-3.7249]**	[7.0353]**	[6.8377]**	[7.5424]**
HML	0.273079	-0.20686	-0.04041	0.014101	0.059303
	[3.3614]**	[-4.3291]**	[-0.8279]	[0.3808]	[1.6899]
R-squared:	0.7738	0.8756	0.8131	0.8258	0.8294
Eq Name:	**DOWNSIDECAPM6B**	**DOWNSIDECAPM7B**	**DOWNSIDECAPM8B**	**DOWNSIDECAPM9B**	**DOWNSIDECAPM10B**
Dep. Var:	YT6	YT7	YT8	YT9	YT10

XT	1.055771	0.949571	0.955847	0.982622	1.049073
	[33.2407]**	[31.2745]**	[28.4940]**	[22.4513]**	[28.2544]**
SMB	0.347492	0.3318	0.361297	0.416687	0.253658
	[6.4353]**	[7.6981]**	[7.4589]**	[7.3493]**	[5.9824]**
HML	-0.05697	0.007967	0.135176	0.264551	-0.13113
	[-1.3719]	[0.2882]	[3.3277]**	[4.4469]**	[-2.4588]*
R-squared:	0.8395	0.8471	0.8414	0.817	0.8149
Eq Name:	**DOWNSIDECAPM11B**	**DOWNSIDECAPM12B**	**DOWNSIDECAPM13B**	**DOWNSIDECAPM14B**	**DOWNSIDECAPM15B**
Dep. Var:	YT11	YT12	YT13	YT14	YT15
XT	1.01995	0.948109	0.904336	1.006108	0.957096
	[17.1471]**	[18.1237]**	[27.1164]**	[21.2962]**	[17.4204]**
SMB	0.249126	0.217238	0.248142	0.261565	0.211505
	[4.4195]**	[5.5998]**	[5.7738]**	[5.1429]**	[4.8921]**
HML	-0.05734	-0.00877	0.074931	0.25567	-0.01434
	[-1.1682]	[-0.2123]	[1.9217]	[3.2835]**	[-0.4368]
R-squared:	0.8273	0.8358	0.8373	0.8113	0.8416
Eq Name:	**DOWNSIDECAPM16B**	**DOWNSIDECAPM17B**	**DOWNSIDECAPM18B**	**DOWNSIDECAPM19B**	**DOWNSIDECAPM20B**
Dep. Var:	YT16	YT17	YT18	YT19	YT20
XT	0.878265	0.917386	0.910576	0.902387	0.904344
	[16.5934]**	[22.2478]**	[21.8212]**	[21.2937]**	[20.8532]**
SMB	0.072994	0.04856	0.052593	0.060481	0.055922
	[1.8295]	[1.3918]	[1.4188]	[1.5490]	[1.4336]
HML	-0.02344	-0.0332	-0.03542	-0.05882	-0.00247
	[-0.6083]	[-1.0052]	[-0.9795]	[-1.3589]	[-0.0682]
R-squared:	0.7994	0.8653	0.8379	0.8094	0.8181

Eq Name:	DOWNSIDECAPM21B	DOWNSIDECAPM22B	DOWNSIDECAPM23B	DOWNSIDECAPM24B	DOWNSIDECAPM25B
Dep. Var:	YT21	YT22	YT23	YT24	YT25
XT	0.894077	0.889756	0.86526	0.864952	0.899365
	[20.7463]**	[20.3262]**	[18.1611]**	[18.2144]**	[20.6981]**
SMB	0.123686	0.070441	0.124306	0.100653	0.062451
	[2.7184]**	[1.6300]	[2.3727]*	[1.9737]*	[1.3965]
HML	-0.00261	-0.04047	0.019573	0.008413	0.001025
	[-0.0699]	[-1.0806]	[0.5213]	[0.2188]	[0.0289]
R-squared:	0.8054	0.801	0.7864	0.7546	0.8088

9.11.9 India CAPM 6 and Segregated Portfolios

Eq Name:	CAPM1	CAPM2	CAPM3
Dep. Var:	PORTFOLIO_1-RF	PORTFOLIO_2-RF	PORTFOLIO_3-RF
C	-0.00852	-0.03885	0.197044
	[-0.0135]	[-0.4083]	[0.5988]
RM_RF	1.166279	0.962958	1.075432
	[11.5273]**	[73.4303]**	[27.4718]**
R-squared:	0.4235	0.972	0.7746
Eq Name:	**CAPM4**	**CAPM5**	**CAPM6**
Dep. Var:	PORTFOLIO_4-RF	PORTFOLIO_5-RF	PORTFOLIO_6-RF
C	0.375006	0.505953	-0.02805
	[1.2312]	[1.1941]	[-0.1080]
RM_RF	1.049592	1.162694	1.002538
	[18.5784]**	[24.6855]**	[31.8380]**
R-squared:	0.7827	0.6509	0.8133

Eq Name:	CAPM11	CAPM12	CAPM13	CAPM14
Dep. Var:	PORTFOLIO_1-RF	PORTFOLIO_1-RF	PORTFOLIO_1-RF	PORTFOLIO_1-RF
C	0.141961	1.700178	0.088702	-1.57994
	[0.1560]	[0.8939]	[0.0789]	[-1.7136]
RM_RF	1.259149	1.027185	1.070453	1.655097
	[8.4055]**	[4.3363]**	[8.8912]**	[9.1603]**
R-squared:	0.6429	0.2276	0.6818	0.518
Eq Name:	**CAPM21**	**CAPM22**	**CAPM23**	**CAPM24**
Dep. Var:	PORTFOLIO_2-RF	PORTFOLIO_2-RF	PORTFOLIO_2-RF	PORTFOLIO_2-RF
C	0.211209	-0.40116	-0.00348	-0.02198

	[1.0285]	[-2.5400]*	[-0.0252]	[-0.2475]
RM_RF	0.927835	1.011102	0.96059	0.915613
	[29.5870]**	[64.6713]**	[57.7482]**	[47.8812]**
R-squared:	0.9543	0.9766	0.9823	0.9726
Eq Name:	**CAPM31**	**CAPM32**	**CAPM33**	**CAPM34**
Dep. Var:	PORTFOLIO_3-RF	PORTFOLIO_3-RF	PORTFOLIO_3-RF	PORTFOLIO_3-RF
C	-1.17134	1.13608	0.032161	0.47053
	[-1.9363]	[1.9596]	[0.0620]	[1.2332]
RM_RF	0.853021	1.028786	1.141309	1.400281
	[11.4729]**	[14.8105]**	[21.0396]**	[19.1899]**
R-squared:	0.6755	0.7565	0.8541	0.8179
Eq Name:	**CAPM41**	**CAPM42**	**CAPM43**	**CAPM44**
Dep. Var:	PORTFOLIO_4-RF	PORTFOLIO_4-RF	PORTFOLIO_4-RF	PORTFOLIO_4-RF
C	0.127078	1.750933	0.219504	-0.26307
	[0.3179]	[2.5743]*	[0.5265]	[-0.6742]
RM_RF	1.17918	0.870641	1.033707	1.339926
	[21.9443]**	[9.4954]**	[19.8077]**	[12.3127]**
R-squared:	0.8911	0.6184	0.8886	0.7972
Eq Name:	**CAPM51**	**CAPM52**	**CAPM53**	**CAPM54**
Dep. Var:	PORTFOLIO_5-RF	PORTFOLIO_5-RF	PORTFOLIO_5-RF	PORTFOLIO_5-RF
C	-1.44987	1.695773	1.014441	0.190435
	[-1.9755]	[1.7971]	[1.2515]	[0.3680]
RM_RF	0.838723	1.208293	1.206389	1.41303
	[9.3224]**	[11.3922]**	[15.9352]**	[14.1556]**
R-squared:	0.5726	0.6295	0.7094	0.7132
Eq Name:	**CAPM61**	**CAPM62**	**CAPM63**	**CAPM64**
Dep. Var:	PORTFOLIO_6-RF	PORTFOLIO_6-RF	PORTFOLIO_6-RF	PORTFOLIO_6-RF
C	-0.58816	-0.10603	0.002368	0.380016
	[-1.1047]	[-0.2010]	[0.0052]	[1.3824]
RM_RF	0.885317	1.025725	1.023758	1.09725
	[11.9666]**	[16.8879]**	[15.8186]**	[19.9735]**
R-squared:	0.7474	0.7981	0.8586	0.8416

9.11.10India CAPM FF 6 and Segregated Portfolios

Eq Name:	**CAPM12**	**CAPM22**	**CAPM32**
Dep. Var:	PORTFOLIO_1-RF	PORTFOLIO_2-RF	PORTFOLIO_3-RF
C	-0.6227	0.051545	-0.04266
	[-1.4032]	[0.7931]	[-0.2533]
RM_RF	1.018937	0.988187	0.980739

	[14.2285]**	[85.0695]**	[39.8244]**
SMB	-0.7004	-0.03346	0.562062
	[-6.0270]**	[-2.3374]*	[12.5506]**
HML	1.100095	-0.12083	0.315356
	[10.9374]**	[-11.8458]**	[8.0420]**
R-squared:	0.6391	0.9836	0.943
Eq Name:	**CAPM42**	**CAPM52**	**CAPM62**
Dep. Var:	PORTFOLIO_4-RF	PORTFOLIO_5-RF	PORTFOLIO_6-RF
C	0.106481	-0.01972	-0.08682
	[0.4699]	[-0.2347]	[-0.5786]
RM_RF	1.001938	0.984598	0.953981
	[23.1546]**	[80.5111]**	[38.3264]**
SMB	-0.36541	0.729012	0.569402
	[-5.0345]**	[21.0519]**	[13.7662]**
HML	0.363886	0.696956	0.072706
	[6.1821]**	[33.6940]**	[2.0909]*
R-squared:	0.8501	0.9853	0.9349

Eq Name:	**CAPM11B**	**CAPM12B**	**CAPM13B**	**CAPM14B**
Dep. Var:	PORTFOLIO_1-RF	PORTFOLIO_1-RF	PORTFOLIO_1-RF	PORTFOLIO_1-RF
C	0.329157	-1.20067	-0.03439	-0.77052
	[0.3995]	[-0.8230]	[-0.0330]	[-1.8126]
RM_RF	1.1641	1.114553	0.966918	0.962784
	[10.4117]**	[5.8031]**	[8.0714]**	[8.5613]**
SMB	-0.22776	-0.83704	-0.41129	-1.03993
	[-1.4992]	[-3.1290]**	[-1.1382]	[-7.0929]**
HML	1.041793	1.183528	0.761332	1.127224
	[7.6169]**	[7.1516]**	[2.6086]*	[9.6055]**
R-squared:	0.7722	0.4767	0.7498	0.8858
Eq Name:	**CAPM21B**	**CAPM22B**	**CAPM23B**	**CAPM24B**
Dep. Var:	PORTFOLIO_2-RF	PORTFOLIO_2-RF	PORTFOLIO_2-RF	PORTFOLIO_2-RF
C	-0.01248	-0.10874	0.122616	0.009275
	[-0.0771]	[-0.9044]	[1.3142]	[0.1252]
RM_RF	0.90932	1.0214	0.99179	0.973219
	[34.7269]**	[76.0037]**	[84.8266]**	[52.4038]**
SMB	-0.12261	-0.00397	-0.01382	-0.07055
	[-3.7787]**	[-0.2028]	[-0.4748]	[-3.2166]**
HML	-0.15747	-0.11801	-0.12878	-0.09788
	[-3.4163]**	[-6.2648]**	[-6.1255]**	[-5.5487]**
R-squared:	0.9742	0.9877	0.9923	0.9833
Eq Name:	**CAPM31B**	**CAPM32B**	**CAPM33B**	**CAPM34B**

Dep. Var:	PORTFOLIO_3-RF	PORTFOLIO_3-RF	PORTFOLIO_3-RF	PORTFOLIO_3-RF
C	-0.07472	0.385954	-0.23478	0.079033
	[-0.3276]	[1.1064]	[-0.9544]	[0.4375]
RM_RF	0.994657	0.911346	1.036566	1.193418
	[39.7383]**	[25.1674]**	[41.2744]**	[28.0099]**
SMB	0.753103	0.473778	0.637679	0.698295
	[15.0107]**	[8.2630]**	[7.6139]**	[13.5879]**
HML	0.353241	0.331731	0.136044	0.363081
	[6.0365]**	[5.8323]**	[1.9970]*	[7.5151]**
R-squared:	0.963	0.9278	0.9692	0.9609
Eq Name:	**CAPM41B**	**CAPM42B**	**CAPM43B**	**CAPM44B**
Dep. Var:	PORTFOLIO_4-RF	PORTFOLIO_4-RF	PORTFOLIO_4-RF	PORTFOLIO_4-RF
C	-0.00949	0.659109	-0.07975	-0.20678
	[-0.0225]	[1.1545]	[-0.2416]	[-0.5386]
RM_RF	1.127885	0.937643	0.9888	1.17532
	[17.9201]**	[13.3744]**	[22.8575]**	[11.0746]**
SMB	-0.19437	-0.52227	-0.42537	-0.03033
	[-1.9648]	[-4.2948]**	[-4.1823]**	[-0.2913]
HML	0.233078	0.406995	0.408486	0.273658
	[2.4489]*	[3.5419]**	[5.7830]**	[2.9081]**
R-squared:	0.9048	0.7743	0.9238	0.8254
Eq Name:	**CAPM51B**	**CAPM52B**	**CAPM53B**	**CAPM54B**
Dep. Var:	PORTFOLIO_5-RF	PORTFOLIO_5-RF	PORTFOLIO_5-RF	PORTFOLIO_5-RF
C	-0.14965	-0.03782	0.201361	-0.28241
	[-0.8391]	[-0.1792]	[1.9759]	[-2.2809]*
RM_RF	0.977424	1.017295	0.974211	1.001373
	[43.2734]**	[30.0466]**	[104.9964]**	[31.7817]**
SMB	0.805566	0.685376	0.576509	0.901722
	[18.2923]**	[13.8576]**	[16.3125]**	[19.2129]**
HML	0.659451	0.741019	0.720989	0.709832
	[15.7320]**	[25.7843]**	[29.6750]**	[21.5974]**
R-squared:	0.98	0.9833	0.9962	0.9825
Eq Name:	**CAPM61B**	**CAPM62B**	**CAPM63B**	**CAPM64B**
Dep. Var:	PORTFOLIO_6-RF	PORTFOLIO_6-RF	PORTFOLIO_6-RF	PORTFOLIO_6-RF
C	0.361148	-0.25655	-0.02342	0.102602
	[1.4242]	[-0.6709]	[-0.0906]	[0.6427]
RM_RF	1.040649	0.912721	0.967728	0.983238
	[38.6429]**	[24.0882]**	[31.2076]**	[26.8349]**
SMB	0.74973	0.550596	0.783495	0.483068
	[14.5471]**	[9.8359]**	[7.8560]**	[12.9371]**

HML	0.036401	0.095077	-0.14891	0.20267
	[0.6585]	[2.3182]*	[-1.8831]	[4.5631]**
R-squared:	0.9514	0.918	0.9622	0.9474

9.11.11 India Downside Beta 6 and Segregated Portfolios

Eq Name:	**DOWNSIDECAPM11**	**DOWNSIDECAPM21**	**DOWNSIDECAPM31**
Dep. Var:	YT1	YT2	YT3
XT	1.199983	0.954746	1.115162
	[11.3811]**	[67.4127]**	[28.2242]**
R-squared:	0.3736	0.9664	0.815
Eq Name:	**DOWNSIDECAPM41**	**DOWNSIDECAPM51**	**DOWNSIDECAPM61**
Dep. Var:	YT4	YT5	YT6
XT	1.042076	1.195259	1.053688
	[19.2751]**	[23.3804]**	[27.2709]**
R-squared:	0.7651	0.7041	0.8565

Eq Name:	**DOWNSIDECAPM 11**	**DOWNSIDECAPM 12**	**DOWNSIDECAPM 13**	**DOWNSIDECAP M14**
Dep. Var:	YT11	YT12	YT13	YT14
XT1	1.44734	1.067134	1.095312	1.588409
	[6.4563]**	[5.9631]**	[6.2762]**	[6.1439]**
R-squared:	0.5569	0.121	0.6826	0.3065
Eq Name:	**DOWNSIDECAPM 21**	**DOWNSIDECAPM 22**	**DOWNSIDECAPM 23**	**DOWNSIDECAP M24**
Dep. Var:	YT21	YT22	YT23	YT24
XT1	0.914111	0.996669	0.950804	0.921259
	[23.0180]**	[60.7838]**	[50.0186]**	[38.2688]**
R-squared:	0.9341	0.9716	0.9806	0.9638
Eq Name:	**DOWNSIDECAPM 31**	**DOWNSIDECAPM 32**	**DOWNSIDECAPM 33**	**DOWNSIDECAP M34**
Dep. Var:	YT31	YT32	YT33	YT34
XT1	0.922755	1.035128	1.175397	1.487009
	[14.5988]**	[15.5538]**	[19.0487]**	[18.5674]**

R-squared:	0.7306	0.8161	0.8803	0.8406
Eq Name:	**DOWNSIDECAPM41**	**DOWNSIDECAPM42**	**DOWNSIDECAPM43**	**DOWNSIDECAPM44**
Dep. Var:	YT41	YT42	YT43	YT44
XT1	1.19632	0.89453	1.036437	1.182291
	[12.4089]**	[8.9154]**	[13.9607]**	[11.7892]**
R-squared:	0.8238	0.6365	0.9013	0.6514
Eq Name:	**DOWNSIDECAPM51**	**DOWNSIDECAPM52**	**DOWNSIDECAPM53**	**DOWNSIDECAPM54**
Dep. Var:	YT51	YT52	YT53	YT54
XT1	0.945177	1.170882	1.264126	1.502057
	[10.6247]**	[10.3575]**	[18.9780]**	[12.9707]**
R-squared:	0.6045	0.5906	0.8178	0.7526
Eq Name:	**DOWNSIDECAPM61**	**DOWNSIDECAPM62**	**DOWNSIDECAPM63**	**DOWNSIDECAPM64**
Dep. Var:	YT61	YT62	YT63	YT64
XT1	0.937453	1.054329	1.063158	1.240318
	[16.7037]**	[14.8120]**	[14.5228]**	[20.2903]**
R-squared:	0.8133	0.845	0.8834	0.8991

9.11.12India Downside Beta 6 FF and Segregated Portfolios

Eq Name:	**CAPMD1**	**CAPMD2**	**CAPMD3**
Dep. Var:	YT1	YT2	YT3
XT	1.325915	0.958704	1.094512
	[12.6826]**	[73.4853]**	[32.5869]**
HML	0.291647	-0.0503	0.078528
	[4.3726]**	[-5.3829]**	[3.6315]**
SMB	-0.22403	-0.0035	0.126557
	[-2.5886]*	[-0.3651]	[4.0316]**
R-squared:	0.4476	0.9709	0.8534
Eq Name:	**CAPMD4**	**CAPMD5**	**CAPMD6**
Dep. Var:	YT4	YT5	YT6
XT	1.144774	1.189123	1.062739
	[22.5935]**	[26.9677]**	[32.3894]**

HML	0.101483	0.14206	-0.0075
	[4.2921]**	[4.7976]**	[-0.4552]
SMB	-0.15242	0.138647	0.152163
	[-4.5552]**	[3.4367]**	[5.4178]**
R-squared:	0.788	0.7842	0.8831

Eq Name:	**DOWNSIDECAPM 11B**	**DOWNSIDECAPM 12B**	**DOWNSIDECAPM 13B**	**DOWNSIDECAP M14B**
Dep. Var:	YT11	YT12	YT13	YT14
XT	1.403837	1.196989	1.063349	1.339694
	[6.3715]**	[7.7398]**	[6.1872]**	[7.6388]**
SMB	-0.0334	-0.50327	-0.33746	-0.52814
	[-0.4699]	[-2.2614]*	[-1.3098]	[-3.0341]**
HML	0.29273	0.273218	0.407472	0.452872
	[2.4730]*	[2.2616]*	[2.0088]	[2.8508]**
R-squared:	0.5821	0.2292	0.7315	0.5724
Eq Name:	**DOWNSIDECAPM 21B**	**DOWNSIDECAPM 22B**	**DOWNSIDECAPM 23B**	**DOWNSIDECAP M24B**
Dep. Var:	YT21	YT22	YT23	YT24
XT	0.921842	0.990453	0.959322	0.945736
	[23.3198]**	[60.5815]**	[56.9932]**	[38.7638]**
SMB	-0.04186	-0.00289	-0.00074	-0.02589
	[-2.6108]*	[-0.2240]	[-0.0256]	[-1.5645]
HML	-0.06356	-0.03965	-0.04508	-0.04036
	[-2.4782]*	[-2.4928]*	[-2.2132]*	[-3.0584]**
R-squared:	0.9447	0.975	0.9834	0.9694
Eq Name:	**DOWNSIDECAPM 31B**	**DOWNSIDECAPM 32B**	**DOWNSIDECAPM 33B**	**DOWNSIDECAP M34B**
Dep. Var:	YT31	YT32	YT33	YT34
XT	0.909134	1.041008	1.143506	1.43316
	[18.1886]**	[18.2904]**	[23.6465]**	[18.8037]**
SMB	0.173146	0.082863	0.309327	0.173414
	[3.1695]**	[1.4683]	[2.7812]**	[3.0317]**
HML	0.135988	0.116313	-0.04682	0.082507

	[2.8079]**	[2.9570]**	[-0.7835]	[1.8315]
R-squared:	0.8108	0.8522	0.9108	0.8647
Eq Name:	**DOWNSIDECAPM 41B**	**DOWNSIDECAPM 42B**	**DOWNSIDECAPM 43B**	**DOWNSIDECAP M44B**
Dep. Var:	YT41	YT42	YT43	YT44
XT	1.18351	0.954376	1.03806	1.111876
	[12.0953]**	[9.4207]**	[18.4540]**	[10.5207]**
SMB	-0.10883	-0.22134	-0.24764	-0.07456
	[-2.3128]*	[-2.3928]*	[-3.1454]**	[-1.1222]
HML	0.062291	0.136695	0.165453	0.124165
	[1.0747]	[2.2380]*	[3.4440]**	[2.1811]*
R-squared:	0.8338	0.6939	0.9197	0.6882
Eq Name:	**DOWNSIDECAPM 51B**	**DOWNSIDECAPM 52B**	**DOWNSIDECAPM 53B**	**DOWNSIDECAP M54B**
Dep. Var:	YT51	YT52	YT53	YT54
XT	0.912596	1.174145	1.214121	1.366464
	[14.0165]**	[12.5978]**	[21.1994]**	[13.6804]**
SMB	0.193522	0.212274	0.285011	0.182285
	[3.0414]**	[2.3678]*	[2.3388]*	[2.1823]*
HML	0.271998	0.228093	0.067238	0.221497
	[3.5371]**	[3.7107]**	[0.8665]	[3.3385]**
R-squared:	0.7505	0.7065	0.8635	0.8153
Eq Name:	**DOWNSIDECAPM 61B**	**DOWNSIDECAPM 62B**	**DOWNSIDECAPM 63B**	**DOWNSIDECAP M64B**
Dep. Var:	YT61	YT62	YT63	YT64
XT	0.931777	1.030368	1.041847	1.220281
	[19.1371]**	[15.7825]**	[20.2226]**	[22.5071]**
SMB	0.150076	0.150092	0.344798	0.092062
	[3.5405]**	[2.3138]*	[3.2287]**	[2.3274]*
HML	0.075483	0.005725	-0.12839	0.029214
	[1.9315]	[0.1652]	[-2.2019]*	[1.0229]
R-squared:	0.8636	0.8654	0.916	0.9075