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Fama and French Three-Factor model: Application to Greek Stock Market.

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Fama and French Three-Factor model: Application to Greek Stock Market.

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Abstract

This study empirically examines the Fama and French three-factor model of stock returns for Greek stock market. We find evidence of market, size and book-to-market explanatory power for Greek stock returns. We use time series regression and find that mean returns are explained by exposures to these three factors and not only the market factor alone. We also estimate the model using non-linear methods, like GARCH model, and we find consistency with linear regression models. The empirical results, as whole, are reasonably consistent with the Fama and French three-factor model.

1. Introduction

Fama and French (1992) find that the main prediction of the CAPM, a linear cross-sectional relationship between mean excess returns and exposures to the market factor, is violated for the US stock market. Exposures to two other factors, a size based factor and a book-to-market-based factor, often called a “value” factor, explain a significant part of the cross-sectional dispersion in mean returns. Size and book to market ratio are both highly correlated with the average returns of common stocks. Fama and French (1993) argue that these effects are proxies for factors of risk. If stocks are priced rationally, then systematic differences in average returns should be due to differences in risk. Thus, given rational pricing, the market, size and value exposures must proxy for sensitivity to pervasive risk factors in returns. Fama and French (1992) found that portfolios constructed to mimic size and value risk factors help to explain the random returns to stock portfolios, using US data.

This master thesis examines the validity of the three-factor model for Greek stock market for a ten-year period from June 2001 until June 2011. Monthly portfolio returns are regressed on market, size and book-to-market ratios**.** We test the market - factor linear pricing relationship implied by the CAPM, the size and book-to-market factors relationship with average stock returns and the three-factor linear pricing model of Fama and French.

Our results show that the three-factor model explains better the common variation in stock returns than the capital asset pricing model. Moreover both the CAPM and the three-factor model do a good job in explaining the cross section of stock returns. We also test the existence of volatily in structure by using non-linear regressions, based on maximum likehood estimator, because of the existence of ARCH effects. We find that the GARCH models give better coefficient estimates and correct any heteroskedasticity and autocorrelation lag values that appear with the usual OLS method. Lastly we compare risk factors estimates taken from all estimating methods and we find further evidence of three-factor model robustness.

In section 2 we report the theory behind investment decisions. We also present the theory behind the most widely used asset pricing models, including three-factor model. In section 3 we represent scientific report papers about the importance of size and book-to-market risk factors to portfolio returns, and the research for three-factor model robustness in several stock markets. In section 4 we describe our data and its sources. We also conduct some descriptive statistics tests. In section 5 we examine whether market factor, size and book-to-market factors have explanatory power for average stock returns. We also conduct some more tests about autocorrelation and heteroskedasticity in time series regressions and we estimate 4 non-linear GARCH models. Lastly we collect all risk factors coefficient estimates and we compare their values. Summary and concluding remarks are provided in section 6.

2. Theoretical Background

One of the major advances in the investment field during the past few decades has been the recognition that the creation of an optimum investment portfolio is not simply a matter of combining a lot of unique individual securities that have desirable risk-return characteristics. Specifically, it has been shown that you must consider the relationship among the investments if you are going to build an optimum portfolio that will meet your investment objectives.

An investment in financial assets represents the current commitment of an investor's funds for a future period of time in order to earn a flow of funds that compensates for two factors: the time the funds are committed and the risk involved. In effect, investors are trading a known present value (the purchase price of an asset) for some expected future value – that is, one known with certainty.

An investor is always faced with the problem of selection among an enormous number of securities, but rational portfolio choice hide basic principles that help decision makers to structure the problems that exist in portfolio forming.

For most decision problems the selection of criteria to choose among alternatives is important to reach the solution. Investors must estimate and manage the returns and risk from their investments. Under certainty these problems are easy to solve. Finding investor's opportunity set and each indifference curve leads to the solution.

However uncertainty is the most common situation found in our world. Risk, or the change that some unfavorable event will occur, is involved when investment decision are made. One basic assumption of portfolio theory is that as an investor you want to maximize the returns from your investments for a given level of risk. The full spectrum of investments must be considered because the returns from all these investments interact, and this relationship between the returns for assets in the portfolio is important. Hence, a good portfolio is not simply a collection of individually good investments. Portfolio theory also assumes that investors are basically risk averse, meaning that, given a choice between two assets with equal rates of return, they will select the asset with the lower level of risk. This does not imply that everybody is risk averse or that investors are completely risk averse regarding all financial commitments. The combination of risk preference and risk aversion can be explained by an attitude toward risk that depends on the amount of money involved. While recognizing this diversity of attitudes, our basic assumption is that most investors committing large sums of money to developing an investment portfolio are risk averse. To value an asset in a world that moves uncertain, we have to account the risk of its payments. Notably, this is also what we generally find in terms of long-run historical results—that is, there is generally a positive relationship between the rates of return on various assets and their measures of risk. The payoff of an investment is described by a set of outcomes and their probability of occurrence, which is known as a return distribution. The most known and used attributes of return distribution are expected return and standard deviation. Expected return describes the return expected by investors over some future holding period. Standard deviation describes how far the actual value may be from the expected one.

Investors want to maximize their utility according to a certain risk they take, while creating a portfolio through a group of securities. Markowitz (1952) developed the basic portfolio principles that underline the modern portfolio theory (MPT). The primary impact of MPT is on portfolio management because it provides a framework for the systematic selection of portfolios based on expected return and risk principles. Markowitz sought to answer a very basic question: is the risk of a portfolio equal to the sum of risks of the individual assets ? He was the first to develop a specific measure of portfolio risk and to derive the expected return and risk for a portfolio based on covariance relationships.

Portfolio risk is not simply a weighted average of the individual security risks. Markowitz (1952) suggested that we must search for the interrelationships among security returns in order to calculate portfolio risk and to reduce it for a given level of return. This portfolio variance formula indicated the importance of diversifying your investment to reduce the total risk of a portfolio but also showed how to effectively diversify. Diversification is the key to the management of portfolio risk because it allows investors to significantly lower portfolio risk without adversely affecting return.

The Markowitz model is based on several assumptions regarding investor behavior:

1. Investors consider each investment alternative as being represented by a probability distribution of expected returns over some holding period.

2. Investors maximize one-period expected utility, and their utility curves demonstrate diminishing marginal utility of wealth.

3. Investors estimate the risk of the portfolio on the basis of the variability of expected returns.

4. Investors base decisions solely on expected return and risk, so their utility curves are a function of expected return and the expected variance (or standard deviation) of returns only.

5. For a given risk level, investors prefer higher returns to lower returns. Similarly, for a given level of expected return, investors prefer less risk to more risk.

Under these assumptions, Markowitz was first to derive the concept of an efficient portfolio, defined as one that has the smallest portfolio risk for a given level of expected return or the largest expected return for a given level or risk. Rational investors will seek efficient portfolios because these are optimized on the two dimensions of most importance to investors, expected return and risk. Using the inputs we described before, expected return, variances and covariance's, we can calculate the portfolio with the smallest variance, or risk, for a given level of expected return based on these inputs. Given the minimum-variance portfolios, we can plot the minimum variance frontier, known as the efficient frontier. This is shown graphically at figure 1:

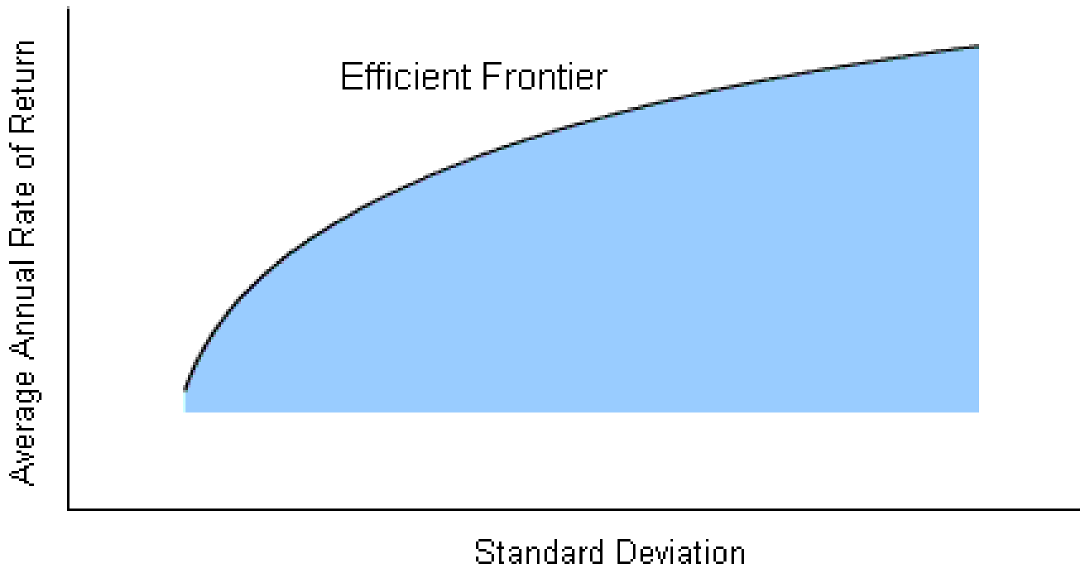

Figure 1

Unfortunately MPT has some serious disadvantages. MPT assumes that all investors are risk averse. Second it is assumed that only the expected return and volatility is important for the investor. Also it is assumed that assets returns are statistically independent, which means that prices are a martingale process.

2.1 The Single Index Model (SIM)

Sharpe (1963) developed the Single Index model. SIM assumes that the returns of all stocks are affected by a common index. That is only one macroeconomic factor that causes the systematic risk, thus no diversifiable risk, affecting all stock returns and this factor can be represented by the rate of return on a market index. According to this model, the return of any asset can be decomposed into the expected excess return of the individual stock due to firm-specific factors, which is denoted as "α", the return due to macroeconomic events that affect the market, and the unexpected microeconomic events that affect only the firm. The return of the stock is:

$$r_i = a_i + \beta_i r_m + e_i$$

The term r_m is the return of market portfolio and $\beta_i \, r_m$ is the market-related part, which expresses the stock's return due to the movement of the market modified by the stock's beta. Macroeconomic events, such as interest rates or the cost of labor causes the systematic risk that affects the returns of all stocks, and the firm-specific events are the unexpected microeconomic events that affect the returns of specific firms. The β_i term measures the sensitivity of a stock to market movements. The beta coefficient is the ratio of covariance between the market and the selected stock divided by the variance of market return. To use the single index model estimates of the beta for each stock are needed. Also e_i represents the unsystematic risk (thus diversifiable risk) of the security due to firm-specific factors. Investors can construct a diversified portfolio and eliminate part of total risk. As more securities are added, the non systematic risk becomes smaller; the total risk of the portfolio approaches its systematic risk. Since diversification cannot reduce systematic risk, total portfolio risk can be reduced no lower than the total risk of the market portfolio.

The single index model has also some assumptions. First it is assumed that r_m and e_i are random variables and unrelated. Also the residual errors for security i are uncorrelated with those of security j; this can be expressed as $\mathrm{Cov}(e_i, ej) = 0$. This is the key assumption of the single index model because it implies that stocks covary together only because of their common relationship to the market index.

2.2 The Capital Asset Pricing Model (CAPM).

The Capital Asset Pricing Model, known as CAPM, was developed by Treynor (1961), Sharpe (1964), Litner (1965) and Mossin (1966) building on the works of Markovitz on diversification and MPT. It is probably the most widely used and known asset pricing model, used for stock selection and portfolio performance evaluation.

Capital market theory is a positive theory in that hypothesizes how investors should behave, as in the case of MPT. It is reasonable to view capital market theory as an extension of portfolio theory, but MPT is not based on the validity of capital market theory.

The CAPM begins where modern portfolio theory ends. Investors choose portfolio of risky assets on the efficient frontier at points where their utility maps are tangent to the frontier. Capital market theory requires some more assumptions:

1. Investors can borrow or lend any amount of money at the risk-free rate of return (RFR).

2. All investors have homogeneous expectations; that is, they estimate identical probability distributions for future rates of return.

3. All investors have the same one-period time horizon such as one month, six months, or one year. CAPM is developed for a single hypothetical period, and its results could be affected by a different assumption. A difference in the time horizon would require investors to derive risk measures and risk-free assets that are consistent with their investment horizons.

4. All investments are infinitely divisible, which means that it is possible to buy or sell fractional shares of any asset or portfolio.

5. There are no taxes or transaction costs involved in buying or selling assets.

6. There is no inflation or any change in interest rates, or inflation is fully anticipated.

7. Capital markets are in equilibrium.

These assumptions appear to be unrealistic and restrict the model. However the model does a good job in explaining the return in risky assets.

The CAPM's main prediction is that market portfolio is mean-variance efficient resulting in a linear cross-sectional relationship between mean excess returns. The equation relationship is:

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

where

R_f	is the risk free rate
$E(R_m)$	is the expected rate of market return
β_ι	is the sensitivity of asset's i return to market return
$E(R_i)$	is the i asset's expected return.

The model implies that the market portfolio is tangent to capital market line. Capital Market Line depicts the equilibrium conditions that prevail in the market for efficient portfolios consisting of the optimal portfolio of risky assets and the risk-free rate. All combinations of the risk-free asset and the risky portfolio are on the CML, and in equilibrium all investors will end up with a portfolio somewhere on CML, depending on their risk attitude. Also the model tells us that investors are rewarded only for holding systematic risk. Unsystematic risk can be removed with diversification.

The role of beta is very important for CAPM. The relevant risk measure for any asset is its covariance with the market portfolio. Beta is a relative measure of risk – the risk of an individual stock relative to the market portfolio off all stocks. The beta coefficient equal with:

$$\beta_i = \frac{Cov\left(R_i, R_m\right)}{Var\left(R_m\right)}$$

which is the covariance of asset I with the market portfolio divided by the market's portfolio variance. Stocks with high beta value are expected to give higher returns than low beta stocks as a result of the risk. The aggregate market has a beta value of 1.0. More volatile stocks have beta's larger than 1.0 and less risky stocks have beta's lower than 1.0. The relationship between and asset's expected return and its beta is described by the Security Market Line (SML). SML is the graphical depiction of the CAPM. The asset's risk and rate of return are connected through a linear relationship.

Deviations from SML indicate abnormal returns and they are measured from Jensen's alpha. According to Fama's (1970) efficient market hypothesis mispricing effects are rejected and deviations from SML are considered to be the reason of other risk factors. Most of the CAPM tests found alphas frequently different from zero, which indicate to presence of abnormal returns and superior or inferior portfolio performance. Tests from Black et. al (1972) and Fama and MacBeth (1973) show that CAPM insufficient on its standard form. Also Fama and French (1992) found two variables that are consistently related to stock returns: the firm's size and its market/book ratio. As an alternative, researchers and practitioners have begun to look to more general multi-beta models that expand on the CAPM. The multi-beta model is an attractive generalization of the traditional CAPM model's insight that market risk, or the risk that cannot be diversified away underlies the pricing of assets. In the multi-beta model, market risk is measured relative to a set of risk factors that determine the behavior of asset returns, whereas the CAPM gauges risk only relative to the market return. It is important to note that the risk factors in the multi-beta model are all nondiversifiable sources of risk. Empirical research investigating the relationship between economic risk factors and security returns is ongoing, but it has discovered several risk factors, including the bond default premium, the bond term structure premium, and inflation, that affect most securities. Practitioners and academicians have long recognized the limitations of the

CAPM, and they are constantly looking for ways to improve it. The multi-beta model is a potential step in that direction.

2.3 Intertemporal Capital Asset Pricing Model (ICAPM).

The intertemporal capital asset pricing model (ICAPM) was presented by Merton in 1973. The model proposes that an asset's expected return is a linear function of several parameters including market portfolio. ICAPM also assumes that investment opportunities change over time and as a result the investor preference for certain assets change also, in contrast with CAPM which is a static model. The models equation form is:

$$E\left(R_i\right) = R_f + \beta_m k_m + \beta_1 k_1 + \beta_2 k_2 + \ldots + \beta_j k_j$$

where

R_f is the risk free rate of return

k_m is the market risk factor

β_m is the sensitivity of portfolio to market portfolio

$E(R_i)$ is the asset's i expected rate of return.

k_j is the j – risk factor

β_j is the sensitivity of asset's I return to j – risk factor.

The risk factors must describe the evolution in investment opportunities and they can be several macroeconomic factors as inflation rate, GDP and several firm specific factors.

2.4 Arbitrage Pricing Theory (APT)

Ross (1976) developed a multifactor model for asset pricing. Arbitrage pricing theory (APT) has emerged as an alternative theory of asset pricing to the CAPM.

APT is based on the law of one price, which states that two otherwise identical assets cannot sell at different prices. Also one of the main assumptions of APT is that efficient market hypothesis holds. The equilibrium market prices will adjust to eliminate any arbitrage opportunities. If arbitrage opportunities arise, relative few investors can act to restore equilibrium.

The APT pricing model does not require assumptions about utility theory or requires specific factors to be included. The APT model is more general than the CAPM with less restrictive assumptions. Unlike CAPM, APT does not assume

- A single-period investment horizon
- The absence of taxes
- Borrowing and lending at the rate of risk-free rate.
- Investors select portfolios on the basis of expected return and variance

APT, like CAPM, does assume:

- Investors have homogenous beliefs
- Investors are risky-averse utility maximizers
- Markets are perfect
- Returns are generated by a factor model.

In some ways, the CAPM can be considered a "special case" of the APT in that the securities market line represents a single-factor model of the asset price, where beta is exposed to changes in value of the market.

The APT assumes that the expected return of a financial asset can be modeled as a linear function of various macro-economic factors or theoretical market indices, where sensitivity to changes in each factor is represented by a factor-specific beta coefficient. Its equation form is:

$$R_i = a_i + b_{i1}F_1 + b_{i2}F_2 + \ldots + b_{in}F_n + e_i$$

where

α_ι is asset's i return when all indices have value of zero

F_n is the value of index k that impacts asset's i's return

b_{in} is the sensitivity of the j-th asset to factor k, also called factor loading,

e_i is the risky asset's idiosyncratic random shock where:

i. $E(e_i e_j) = 0$ for every i,j i # j
ii. $E[e_i (F_j - \underline{F}_j)] = 0.$

It is important to note that the expected value of each factor is zero. The F's are measuring the deviation of each factor from its expected value.

2.5 The Multi-Index Models (MIM).

Multi-index models are an attempt to capture some of the nonmarket influences that cause securities to move together. In that way they try to capture additional information. The search for nonmarket influences is a search for a set of economic factors of structural groups that account for common movement in stock prices beyond that that accounted for by the market index itself. The cost of adding more indexes is the change that they are picking up random noise than real influences.

The equation form of the model is:

$$R_i = a_i + b_{i1}L_1 + b_{i2}L_2 + \ldots + b_{in}L_n + e_i$$

where

α_i is the component of asset's I return that is independent of the factors

L_n is the level of Index j

b_{jn} is the measure of responsiveness of r_j to a change in F_j

e_j is the random noise of asset j.

By construction it holds that:

- $E(e_j) = 0$
- $Cov(F_i, F_j) = 0$
- $Cov(e_i, F_j) = 0$

Also by assumption it holds that: $Cov(e_i, e_j) = 0$.

Theoretically, Multi-Index models lie in an intermediate position between the full historical correlation matrix itself and the Single-Index model in ability to reproduce the historical correlation matrix. The more indexes added, the more complex things become and the more accurately the historical correlation matrix is reproduced. However, this does not imply that future correlation matrices will be forecast more accurately. Since there are infinite numbers of Multi-Index models, we cannot say with certainty that they are better or worse than the Single-Index models.

There are two approaches to construct a multi-index model. The statistical approach involves building factors from a set of asset returns. Data of these returns are use to construct portfolios that represent factors. Purpose of this approach is to construct a specific set of factors so as the covariance of residual returns to be the smallest. The problem that exists in this method is that there is no theory to tell when to stop extracting factors.

An alternative approach is use to reduce the number of variable used, and its called principal components analysis. The analysis extracts from the historical variance-covariance matrix of returns the index that best explains the variance of the original data. The number of principal components we should use is, as in factor, a subjective matter. Adding few factors may lead to information loss and adding too many may add noise to the model.

Another kind of models are macroeconomic models. They specify financial variables that capture the nondiversifiable risk of the economy. Chen, Roll and Ross (1986) found significant relationship between the macroeconomic variables and systematic factors.

2.6 The Fama & French Three-Factor Model (TFM).

Fama and French (1992) examined the joint of market beta, firm size, earnings-to-price ratio, financial leverage and book-to-market equity of value (Banz and Reinganum (1981), Basu (1977), Litzenberg and Ramaswamy (1979), Bhandari (1988), Rosenberg et. al (1985)). in the cross-section of average stock returns. Their results show that used alone or in combination the beta variable had little information about average returns but size, E/P, leverage and book-to-market equity had explanatory power. Especially, size and book-to-market equity seem to absorb the roles of leverage and E/P and have a strong role in determining the cross section of average returns.

Also Fama and French (1993), extended their research by expanding the set of asset returns, by adding US government and corporate bond return series. Also they expanded the set of variables used to explain returns. The size and book-to-market variables are directed at stocks. So they added term-structure variables that are likely to play role in bond returns. According to their research if markets are integrated, variables that explain bond returns help to explain stock returns and vice versa.

One the most important difference, according to their previous research (1992), was the use of time series regressions instead of the cross-section approach of Fama and MacBeth (1973). The cross-section of stock returns is regressed on variables hypothesized to explain average returns. Size and book-to-market variables play no role explaining the bond returns in cross-section regressions. Also time series regressions give direct evidence, of whether variables like size and book-to-market equity, proxy for sensitivity to common risk factors in returns. The time series regressions, also, use excess returns as dependent variables and either excess returns or returns on zero-investment portfolios as explanatory variables. According to Merton (1973) a well specified asset-pricing model gives intercepts estimates close to zero. The intercepts estimates provide evidence of how well different combinations of the common risk factors capture the cross-section of average returns.

Fama and French (1993) discovered that for stocks, portfolios constructed to mimic risk factors of size and book-to-market capture strong common variation in returns. Moreover, intercepts estimations are close to zero for regressions that include excess market return and mimicking portfolio returns for size and book-to-market factors. Also used alone the mimicking portfolios for the two term-structure factors capture strong variation in the stock returns. Interestingly when including stock-market factors, the two term-structure variables do not lose their explanatory power.

Also for bond market regressions the three stock market factors capture common variation in returns. But when the two term-structure factors are included market, size and book-to-market lose their explanatory power for bond returns.

More specifically, for stock market, Fama and French discovered a negative relationship between average returns and firm size and a positive relation with book-to-market ratio. Small and value (high book to value ratio) firms are riskier so investors seek higher rates of returns. Fama and French observed than when investors take into account size and book-to-market factors of a portfolio, the market beta variable is not enough to explain the returns.

According to modern finance, the book value of an asset is the historical value of the firm’s capital. The market value is a better estimate of future cash flows of the firm. Investors want better returns for buying value stocks.

However, opinions differ as to whether the outperformance of value firms is due to market efficiency. The difference comes from whether market efficiency is assumed. The business analysts does not assume that efficient market hypothesis hold so high book/price indicates a buying opportunity: the stock looks cheap. But if we assume that efficient markets exist then cheap stocks can only be cheap for a good reason, namely that investors think they're risky.

The TFM has taken several criticisms in recent years. One problem is the lack of theoretical setting. It does not explain why size and book-to-market are proxies for risk. Another major problem is that that TFM cannot explain the momentum effect which is observed in many markets. The model predicts the reversal of future returns for short-term winners and losers. So the continuation of short-term returns is left unexplained (Maris 2009).

Three-Factor Model portfolio methodology

Fama and French (1993) wanted to find evidence for cross-section variation between stock and bond returns. For their purposes they constructed portfolios to mimic risk factors for stocks and bonds. They created mimicking portfolios for size and book-to-market factors, to mimic risk factors for average stocks returns, and two term-structure portfolios to mimic bond-market factors.

First, in June of every year *t*, they ranked on size (price times share) all NYSE, AMEX, NASDAQ stocks. Then using the median NYSE stock size they split all stocks into two groups: big and small. Afterwards, in December of every year *t-1*, they break the market into three groups according to book-to-market value of equity. The break points are the bottom 30% (Low), middle 40% (Medium) and top 30% (High) of the ranked book-to-market values of NYSE assets. After this classification, Fama and French form six portfolios from the intersection of the two size and three book-to-market groups, for every year, and they estimate the returns of those portfolios.

The next step is to represent size and book-to-market risks. Fama and French constructed two factors: SMB factor to address size risk and HML to address value risk. SMB, which stands for Small Minus Big, is designed to measure the additional return investors have historically received by investing in stocks of companies with relatively small market capitalization. This additional return is referred to as the "size premium." The SMB factor is defined as the difference between the average return of the three "small" firms portfolio and the average return of the three "big" firms portfolio. A positive SMB in a month indicates that small cap stocks outperformed large cap stocks in that month. A negative SMB in a given month indicates the large caps outperformed. For SMB, which is a measure of "size risk", small companies logically should be expected to be more sensitive to many risk factors as a result of their relatively undiversified nature and their reduced ability to absorb negative financial events.

HML, which is short for High Minus Low, has been constructed to measure the "value premium" provided to investors for investing in companies with high book-to-market values. HML is defined as the difference between the average return of the two 'high BE/ME' portfolios and the average return of the two 'low BE/ME' portfolios. The HML factor suggests higher risk exposure for typical "value" stocks (high B/M) versus "growth" stocks (low B/M).

Additionally the market factor is defined as difference between total market return and the risk free rate.

The building steps of the six portfolios that are created from combination of size and book-to-market equity are such, so there is no correlation with the factors; so there is no multicollinearity by construction.

The models equation is:

$$R_{pt} - R_{ft} = \alpha_{pt} + \beta_{\mathrm{p}}(R_{mt} - R_{ft}) + s_p SMB_t + \mathrm{h}_p HML_t + \varepsilon_{pt}$$

where:

R_{pt} is the portfolio's p excess return

R_{ft} is the risk free rate

$R_{pt} - R_{ft}$ is the excess return of portfolio p

β_p is the sensitivity of R_{pt} to a change in market premium $R_{mt} - R_{ft}$

s_p is the sensitivity of R_{pt} to a change in size premium SMB

h_p is the sensitivity of R_{pt} to a change in value premium HML

ε_{pt} is the random noise of portfolio p.

3. Literature Review

As mentioned before, deviations from SML (Security Market Line) are considered to be evidence of other risk factors. During the years research over CAPM deviations conducted, and evidence of multiple risk factors has be found. Basu (1977) found serious relationship between earnings to price (E/P) ratio and stock returns. He found that stocks with E/P generated higher returns than those implied by the CAPM. Also Litzenberg and Ramaswamy (1979) found relationship between dividend yields and stock returns. Bhandari (1988) found that high leverage firms produce higher returns relative to their betas. Fama and French (1995) found relationship between size and book-to-market ratio with earnings.

The BM effect was first documented by Rosenberg et. al (1985), who found a return premium to stocks with high ratios of book value to market value of equity. This BM effect or value premium was confirmed by Davis (1994) for US data and by Chan et al. (1991) and Capaul et. al (1993) for markets outside the USA. Also Chen and Zhang (1998), Capaul et. al (1993), La Porta (1996) found evidence of excess returns in value stocks, at US stock market. However, recent evidence from three European markets failed to find evidence of a BM effect in France, Germany and the UK (Malin and Veeraraghavan, 2004). Also Karanikas (1998) found evidence of BM and dividend yield effect in stock returns of Greek stock market.

The size effect was first documented by Banz (1981) and Reinganum (1981), who found a return premium on small stocks in the USA. They found that “small” stocks had better risk adjusted returns than “big” stocks. The size effect or size premium was later confirmed by Blume and Stambaugh (1983) using US data and by Brown et. al (1983) using Australian data. Glezakos (1993) found evidence of size effect on Greek stock Market. Fletcher (1997) found no significant relationship between size and returns in London Stock Exchange. Nartea et. al (2008) found negative size-return relationship and stronger size effect in January months. Nartea et. al (2009) found a small size effect at New Zealand stock market but a bigger BM effect. Lakonishok and Sharipo (1986) found that beta cannot explain the variation on returns and an important size effect, which loses its significance when January months are eliminated. Further research has become from Chan and Chen (1991), Jagannathan and Wang (1996) , Heston et. al (1999) has showed significant size effect.

On the other hand robustness of CAPM model is showed by Kothari et. al (1995) and MacKinlay (1995), who showed that multifactor models cannot explain deviations from CAPM. All the above findings triggered deeper research for multi-index models in order to capture most of the cross-variation in stock returns.

Fama and French three-factor model is one of the most famous multifactor asset pricing models. Fama and French (1996) strengthen their theory for three-factor model robustness. Also at 1998 they confirmed their theory for several international markets. Moerman (2005) showed that TFM exist in euro-area. Michailidis et. al (2006) Messis et. al (2007) Maris (2009) found evidence of TFM existence, for the Greek stock market. Also Messis et. al (2007) found that the TFM model outperform APT at ASE. Brennan et. al (1998) confirmed the existence of size and book-to-market role in the cross section of returns. Daniel et. al (2001) found a strong value effect in stocks returns using TFM in Japan. Also Barber and Lyon (1997) tested the robustness of TFM for financial and non-financial firms of NYSE, AMEX and NASDAQ. Most researches excluded financial firms from TFM testing because financial firms appear to have high leverage. They found that size and book-to-market factors played an important role in explaining portfolio returns in both financial and non-financial firms. Also Malin and Veeraraghavan (2004) found that the beta of CAPM was not sufficient to describe the variation of average returns. Size and book-to-market factors were important for France, Germany and UK stock markets. Nartea et. al (2008) found that TFM was more robust than CAPM for Hong Kong stock market. Similar results were found from Nartea et. al (2009) for New Zealand market. Connor and Sehgal (2001) and Ajili (2002) found same results for India and France respectively.

However, other studies found serious problems in TFM model explanatory power and robustness. Kothari et. al (1995) reported a survivorship bias introduced for firm size and book-to-market portfolios. Firms with low size and high book-to-market value do not survive and thus are not included in the databases. Also, they reported a selection bias due to the COMPUSTAT database. In order to address the problem they used an alternative source of data, the Standard & Poors Industry Level Data, and they found that book-to-market factor does not play an important role. Barber and Lyon (1997) also discovered that COMPUSTAT survivor bias affects size and value premium estimate of all firms. But it should be noted that even if the critic of the survivor bias is true, it is not necessarily in favor of the CAPM.

Black (1993) and MacKinlay (1995) argue that the results presented by Fama and French (1993) may be based on data snooping given the variable construction for the characteristics based portfolios. An extrapolation of data can lead to false conclusions that are why we need the out-of- sample tests. Fama and French reject this bias by advancing four arguments: the premium of the financial distress is not special to a particular sample since it is checked for different periods. It was also the subject of many studies made on international data. The size, book to market equity, earning to price and cash flow ratios, indicators of expected incomes (Ball 1978), have a great utility to test models of asset pricing like the CAPM. And in fourth point, the limited number of the anomalies excludes the assumption of data mining.

Another problem according to Daniel and Titman (1997) is that characteristics such as behavioral biases and liquidity explain the cross-section of stock returns rather than the covariance structure of the model. Also Lakonishok et. al (1994) and

Haugen (1995) suggest that the distress (risk) premium is irrational. An interesting approach comes from Cao et. al (2004) where they found evidence that an artificial neural network model outperforms the tree factor model in Shanghai stock market.

Table 1 summarizes the literature review on the field.

4. Data

We are going to investigate the robustness of TFM to the Greek stock market in order to test the explaining power of size and book-to-market factors to average stock returns. We test the model in the case of Greece for a ten-year period. The testing period is starts from June 2001 and ends the June of 2011. Several events happened before 2001. The stock market bubble in 1999 and 2000 caused high volatility and loss of public trust in capital markets. Also at 2001 came the introduction of European Monetary Union, which brought the replacement of national currency (drachma) with euro. Panagiotidis (2005) found evidence that efficient market hypothesis does not hold on Athens Stock Exchange after the introduction of European common currency. Also past volatility is found to be important for big and medium size firms but not for small firms. Finally, in 2008, the burst of world economic crisis resulted a free fall in global stock market and a period of high volatility and uncertainty, which holds until now.

Our data are monthly closing prices of common stocks traded in Athens stock exchange, using the DataStream database. Also market value, shares number in issue multiplied by the share price, and Market-to-Book value are obtained from DataStream (we used market-to-book value and calculated its inverse to obtain the book-to-market value that we are interested). Book-to-market value is the balance sheet value of an equity divided by its market value.

The selected stocks are included in the formation of the FTSE/ASE 20, FTSE/ASE 40 and FTSE/ASE Small Cap index. We started with 279 common equities which are being trading for a ten-year period. We use only active equities and not dead equities, which may lead to survivorship bias. We also remove all equities with unavailable market date, which exposes us to sample selection bias. We include financial and non-financial firms. Most researchers do not include financial firms, because of high leverage (Barber and Lyon 1997). Finally we do not include stocks with negative book value of equity. In the end, we conclude with 227 equities. The sample period is June 2001 until June 2011, which is 120 observations.

Finally, we use the Greece Government 10-year bond index to be the proxy for risk free rate. We obtained monthly bond yields from DataStream.

We are going to use Fama and French methodology without studying the bond market occasion. We are going to regress monthly portfolio returns onto market return and mimicking portfolios for size and book-to-market risk factors. Fama and French use six portfolios formed from stocks on market size and book-to-market equity. They also use those six portfolios to form the portfolios that are needed to mimic the risk factors, size and book-to-market. The size classification groups the stocks into two groups. In June of each year *t* from 2001 to 2011, all ASE stocks are ranked on size (ME). We use the capitalization of June t to from the portfolios for the period, July *t* to June *t+1*. We then use the median sample size to split the stocks into two groups, small (S) and big (B). We also split all stocks into three book-to-market (BE/ME) groups: Low BE/ME, Medium BE/ME, High BE/ME. We use BE/ME equity at the of financial year, December *t-1*, to form the portfolios for period, June t to June *t+1*. We use monthly returns six months after the balance sheet dates because financial statements in Greece must be released at least 20 days before annual stockholders' meeting which must take place within six months after the financial year ends. Thus, by matching accounting data for firms with a financial year-end that falls in year *(t-1)* with the return period starting in July *(t)*, accounting data were available prior to the return period for the firms in our sample. In this way, a possible look-ahead bias is avoided (Banz and Breen: 1986), (Maris 2009). As we said we split the market into three BE/ME groups based on the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high). Fama and French sort firms into two size groups and three BE/ME groups because according to Fama and French (1992), book-to-market equity has a stronger role in average stock returns than size. Also splits are arbitrary defined.

After grouping the stocks we construct six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersection of the two ME and three BE/ME groups. The monthly return of each portfolio is the value-weighted monthly return of the stocks they include. The value weighted portfolios follow the equation:

$$R_{p,m} = \sum_{i=1}^{n} w_{i,t} R_{i,t}$$

where

$R_{p,m}$	is the portfolio p return in month m
$w_{i,t}$	is the weight of stock i in the portfolio p for year t
$R_{i,m}$	is the stock i return in month m
n	is the number of stocks in portfolio p (different for each year).

So S/L portfolio consists of small and low BE/ME (growth) equities, portfolio S/M consists of small and medium BE/ME equities, portfolio S/H consists of small and high BE/ME (value) equities, portfolio B/L consists of big and growth (low BE/ME) equities, portfolio B/M consists of big and medium BE/ME equities, portfolio B/H consists of big and value (high BE/ME) equities. We also calculate, for each month, the total market return as a weighted average of all stocks returns included in the six intersected portfolios, plus the negative book-to-market stocks.

As we referred the tree-factor model involves the use of three factors for explaining common stock returns. The first one is market factor, as proposed by the CAPM. We are going to use the excess return of the market. The other two risk factors are related to size and BE/ME, SMB and HML. SMB (small minus big) portfolio is meant to mimic the risk factor in returns related to size. It is the difference between the simple average monthly return of the three small portfolios and the simple average monthly return of the three big portfolios:

$$SMB = \frac{(SL + SM + SH)}{3} - \frac{(BL + BM + BH)}{3}.$$

This difference will be free of the influence of BE/ME, focusing instead on the difference return behaviors of small and big stocks (Fama and French 1993).

On the other hand HML (High minus Low) portfolio mimic the BE/ME risk factor and is the difference between the average return of two high BE/ME portfolios and the average monthly return of the two low BE/ME portfolios:

$$HML = \frac{(SH - BH)}{2} - \frac{(SL - BL)}{2}$$

The HML is free of the size factor in returns, focusing in the different return behaviors of high and low BE/ME firms.

The risk factors related to size and values are not tradable, so zero investment portfolios are constructed. So SMB measures a small size premium and HML a value firm premium. The success of this procedure can be shown by looking the small correlation between those two risk factors which is ρ = 0, 06.

In Table 2 we can see the number of companies in each portfolio for each year of the sample period. The B/H is the portfolio with big size and high BE/ME ratio stocks, B/M is big and medium BE/ME ratio stocks portfolio, B/L is big and low BE/ME ratio stocks portfolio, S/H is small size and high BE/ME ratio stocks portfolio, S/M is small and medium BE/ME ratio stocks portfolio and S/L is small and low BE/ME ratio stocks portfolio.

Year	*B/H*	*B/M*	*B/L*	*S/H*	*S/M*	*S/L*
01 - '02	*32*	*51*	*30*	*36*	*40*	*38*
02 - '03	*36*	*49*	*28*	*32*	*42*	*40*
03 - '04	*31*	*49*	*33*	*37*	*42*	*35*
04 - '05	*27*	*50*	*36*	*41*	*41*	*32*
05 - '06	*26*	*42*	*45*	*42*	*49*	*23*
06 - '07	*20*	*41*	*52*	*48*	*50*	*16*
07 - '08	*21*	*45*	*47*	*47*	*46*	*21*
08 - '09	*20*	*48*	*45*	*48*	*43*	*23*
09 - '10	*19*	*45*	*49*	*49*	*46*	*19*
10 - '11	*19*	*43*	*51*	*49*	*48*	*17*
Average	***25***	***46***	***41***	***43***	***45***	***26***

Table 2: Sample characteristics: Greece, July 2001 – June 2011

Number of companies in portfolios formed on size and BE/ME.

As we see, small stock portfolios have almost the same number of firms with big stock portfolios. Also we observe that most small size firms have big and medium BE/ME ratios and opposite most big size companies have lower and medium BE/ME ratios. There are 26 S/L companies and their number is increasing as we go to S/M and S/B portfolios (45 S/M and 43 S/H). On the other hand B/H portfolio contains 25 companies and their number is increasing as we go to B/M and B/L portfolios (46 B/M and 41 B/L). According to theory high BE/ME ratios are signals for distressed firms. So according to Table1 small companies tend to be distressed and are not expected to have enough earnings. On the other hand, most big size firms on ASE have low BE/ME ratio and they are expected to be profitable in the future.

In Table 3 we see the excess returns of our six portfolios, market portfolio and SMB, HML mimicking portfolios. We observe that all of them are negative and close to each other. This finding represents the results of world economic crisis that burst in 2008 and holds until the end of sample period. We can also see that all standard deviations are quite small and almost the same for all portfolios. This results show low volatility on portfolio returns. The same volatility on every portfolio can be explained by the same expected returns findings that exist on all portfolios. This means that investors have same rational on every aspect. We also see that the mean excess market return and SMB return are negative (-0.05 and -0.004 respectively). The negative excess market return is another evidence of world economic crisis. The negative value of SMB factor means that on average there is a size effect, but not strong enough. Also the positive HML mean returns value is a value effect consistent with the portfolio returns and Fama and French (1993). So investors can risk by looking at firms with high BE/ME value of equity for better expected returns.

	Summary Statistics for Excess Returns				
	Mean	***St. Deviation***	***Median***	***Max***	***Min***
B/H	-0.048711	0.097754	-0.054335	0.235904	-0.263719
B/M	-0.057352	0.081047	-0.054988	0.140733	-0.255500
B/L	-0.053066	0.084711	-0.039182	0.166185	-0.345012
S/H	-0.053613	0.108337	-0.056815	0.321321	-0.333704
S/M	-0.057885	0.093833	-0.050576	0.194104	-0.332220
S/L	-0.061897	0.103698	-0.062215	0.167126	-0.384824
Market	-0.056343	0.086363	-0.044531	0.148561	-0.322079
SMB	-0.004755	0.051503	-0.007644	0.143767	-0.115532
HML	0.006319	0.044647	-0.000710	0.157304	-0.076494

Table 3: Sample characteristics: Greece, July 2001 – June 2011
Dependent Variables: Excess Return, Standard Deviation, Median, Maximimum, Minimum.

Also normality tests show that all portfolios, expect B/L and S/H, have average returns normal distributed (see Appendix 1).

We also are going to see the correlation between explanatory variables (Table 4):

Correlation Coefficient (ρ)			
	$\left(R_{mt}-R_{ft}\right)$	***SMB***	***HML***
$\left(R_{mt}-R_{ft}\right)$	1		
SMB	0.006160954	1	
HML	0.185513534	0.064974407	1

Table 4: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Explanatory Variables: Correlation Structure.

Here we see that SMB is almost uncorrelated with excess market return, while HML has a small positive correlation with market return.

We employ the augmented Dickey – Fuller (ADF) unit root test to check for unit root in the series. We checked every variable and we find no evidence of nonstationarity at 10%, 5%, 1% significance levels. The *p*-values of the statistic were zero for all portfolios.

5. Empirical Results

First, we are going to test the explanatory power of market beta on ASE. Results are shown on Table 5:

Empirical CAPM					
$R(t)-R_f(t)=\alpha+\beta\left[E(R_m)-R_f\right]+e(t)$					
	a	***p-value***	***β***	***p-value***	***Adj.*** R^2
B/H	0.007343	0.1533	0.994864***	0.0000	0.770609
B/M	-0.006729***	0.0098	0.898482***	0.0000	0.915936
B/L	0.000234	0.9241	0.945985***	0.0000	0.929544
S/H	0.005657	0.3836	1.051952***	0.0000	0.700707
S/M	-0.007774	0.1907	0.889383***	0.0000	0.667279
S/L	-0.010680	0.1530	0.90902***	0.0000	0.569521

Table 5: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Explanatory Variables: Excess Market Return.

Table 5 shows that the excess return on the market portfolio of stocks captures most of the common variation and most of beta's values are close to one. The important fact is that the market leaves much variation in stock returns that might be explained by other factors. We observe that adjusted R^2 values are low for most portfolios. The only R^2 value near 0.9 are for big and medium, low portfolios. For small portfolios R^2 values are less than 0.7. The intercept values are close to zero for all regression, expect from B/M portfolio, where zero hypothesis is not rejected even on 1% significance level. The intercept values show us that we don't have abnormal returns for most portfolios. Also the intercepts estimates show us how well the average market premium explains the cross-section of average returns on stocks. According to Merton (1973) and Ross (1976) intercepts estimates should be indistinguishable from zero, so as the risk factors suffice to describe the cross-section of average returns. Fama and French found evidence that in higher size portfolios intercepts had lower values than smaller size portfolios. Also they found that higher BE/ME ratio portfolios had bigger intercepts than low BE/ME portfolios. Here we see that most of the small size portfolios have bigger intercepts than big size portfolios, agreeing with Fama and French evidence. Also there doesn't seem to be any difference in intercept values of BE/ME ranked portfolios. Generally, we cannot determine, if intercept values of CAPM, reveal evidence of size and BE/ME factors importance to stocks return explanation, because of the small number of portfolios we use.

Following Fama and French procedure we are going to test if SMB and HML, the mimicking portfolio returns for size and book-to-market factors, can explain the six portfolio returns. If the two risk factors for size and BE/ME are important then the R^2 values should be low and SMB and HML have important coefficient estimates. Results are shown at Table 6:

Two-Factor model							
$R(t)-R_f(t)=\alpha+hHML(t)+sSMB(t)+e(t)$							
	α	p-value	h	p-value	s	p-value	R^2
B/H	0.055185***	0.0000	1.06186***	0.0000	0.049589	0.7473	0.224507
B/M	0.060015***	0.0000	0.436508***	0.0085	0.020216	0.8866	0.042293
B/L	0.054891***	0.0000	0.151373	0.3867	-0.182713	0.2288	0.00076
S/H	0.056001***	0.0000	1.044521***	0.0000	0.885816***	0.0000	0.375693
S/M	0.057794***	0.0000	0.650213***	0.0001	0.883156***	0.0000	0.339073
S/L	0.056295***	0.0000	-0.044993	0.8021	1.118119***	0.0000	0.295521

Table 6: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Explanatory Variables: Size and BE/ME risk factors.

We observe that most R^2 values are lower than 0.35. The HML risk factor is important only for high BE/ME portfolios and its explanatory power is diminishing as we continue to lower BE/ME portfolios. The SMB factor seems to explain some of the returns variation only for small size portfolios, while it loses its power as we move to small size portfolios. So size and book-to-market mimicking portfolios seem to have some explanatory power in Athens stock exchange.

Also the intercepts seem to play an important role on all portfolios. According to Fama and French intercepts that are similar on size, support that size and book-to-market factors explain the strong differences in average returns across stocks.

Lastly we are going to test the explanatory power of all three factors. We are going to use the market portfolio to explain the market risk factor and the two mimicking portfolios for size and book-to-market risk factors, SMB and HML. We conducted White's Heteroskedasticity test on OLS regression and we found the following results Table 7:

White Heteroskedasticity Test						
	B/H	***B/M***	***B/L***	***S/H***	***S/M***	***S/L***
F - Statistic	3.4842	3.8565	1.1505	2.5889	1.5362	2.8128
P - Value	0.0000	0.0001	0.0074	0.0000	0.1875	0.0005

Table 7: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
White Heteroskedasticity Tests: F-Statistic and P-values.

We observe that most p-values are almost to zero, expect S/M portfolio, which is 0.18, So we find evidence for heteroskedasticity for five of the six portfolios. This means that coefficients estimators are no longer BLUE (Best Linear Unbiased Estimator). In order to deal with this problem we re-estimate the regressions using White's heteroskedasticity consistent standard error estimates. Results are shown in Table 8

White heteroskedasticity-consistent standard errors & covariance OLS						
$R_{pt} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + s\, SMB_t + h\, HML_t + \varepsilon_{pt}$						
	High	***Medium***	***Low***	***High***	***Medium***	***Low***
		α			***P-value***	
Big	-0.00094	-0.007975***	0.001742	0.7959	0.0024	0.4214
Small	0.001627	-0.007745***	-0.001055	0.2986	0.0011	0.7677
		b			***P-value***	
Big	0.9247***	0.887106***	0.965397***	0.0000	0.0000	0.0000
Small	0.982365***	0.853171***	0.941667***	0.0000	0.0000	0.0000
		s			***P-value***	
Big	0.058765	0.029019	-0.173134***	0.3915	0.4929	0.0000
Small	0.895565***	0.891622***	1.127463***	0.0000	0.0000	0.0000
		h			***P-value***	
Big	0.729346***	0.117512*	-0.195775***	0.0000	0.0736	0.0000
Small	0.691271***	0.343421***	-0.383608***	0.0000	0.0000	0.0000
		Adjusted R^2			***S.E of Regression***	
	High	***Medium***	***Low***	***High***	***Medium***	***Low***
Big	0.878906	0.919143	0.951664	0.034017	0.023046	0.018624
Small	0.977761	0.944151	0.898664	0.016156	0.022175	0.033011

Table 8: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Explanatory Variables: Market, Size and BE/ME risk factors.

Regressions coefficients of Table 7 provide evidence of the robustness of the three-factor model. First, the intercepts of all six portfolios, expect the medium BE/ME portfolios, are statistically equal to zero. Intercepts that have a value close to 0 say that the regression, which use as explanatory variable R_m, SML, HMB to absorb common time-series variation in return, does a good job explaining the cross-section of average stock returns. According to Fama and French, the average market risk premium absorbs the strong positive intercepts observed in the regressions of stock returns on SMB and HML. So the size and book-to-market factors can explain the differences in average returns across stocks, but the market factor is needed to explain why stock returns are on average above the risk free rate. Secondly, the market factor coefficients are positive and close to one for all six portfolios. The medium size portfolios although they have beta's statistically significant, even on 1% significance level, their values are not so close to one, as the ones of other portfolios. We can assume that intercepts and beta's for the two medium BE/ME portfolios may provide evidence of some other risk factor, or the difficulty of the model to explain average returns. In any case, however, the majority of portfolios have coefficient values that agree with asset pricing theory.

The SMB factor coefficients take positive values in five out of the six regressions. All small stocks portfolios have significant, positive "*s*" coefficients; expect the B/H and B/M portfolios. SMB, the mimicking return for the size factor, clearly captures shared variation in stock returns that is missed by the market and by HML. Also the slopes on SMB for stocks are related to size. We observe that the slopes on SMB decrease from smaller to bigger size stock portfolios. Those findings are consistent with Fama and French (1996) who discovered the same relationship between SMB risk factor and size ranked portfolios.

Similarly the BE/ME factor coefficient (*h* coefficient) are statistically significant, for all but B/M portfolio, where the zero hypothesis is not rejected at 5% significance level. Also low BE/ME ratio stock portfolios have negative and significant *h* coefficients. HML clearly captures shared variation in stock returns, related to book-to-market equity. The results are again consistent with Fama and French, who found that high BE/ME firms load positively and low BE/ME firms load negatively on HML.

Also the model robustness is supported by the increase in adjusted R^2 values. They range from 0.87 to 0.98 with average of 0.93. So 94% of the variation is explained by the three factor model.

Another interesting point is the behavior of market risk factor to the three factor model. Fama and French (1993) discovered that the beta coefficient values converge towards 1.0 when adding SMB and HML mimicking portfolios. This behavior is due to strong correlation that appears between market factor and SMB, HML factors. In our case, however we found little to zero correlation between market portfolio stock returns and the two mimicking, SMB and HML, portfolio returns, which justifies the little change to beta coefficient values.

Also we apply the Schwarz Information criteria to observe which of the three estimating models gives better estimates explaining the variation in stock returns. Results are showed at Table 9:

	Schwarz Information Criteria					
	B/H	**B/M**	**B/L**	**S/H**	**S/M**	**S/L**
CAPM Model	-3.222076	-4.600757	-4.688927	-2.750482	-2.932065	-2.474533
Size and BE/ME factor model	-1.972621	-2.136412	-2.005533	-1.983878	-2.214343	-1.950587
Beta, Size and BE/ME factor model	-3.798243	-4.576954	-5.003048	-5.287361	-4.654025	-3.858295

Table 9: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011 Schwarz Information Criteria values.

According to Schwarz criteria, the model with the lower BIC (Bayesian Information Criterion) is the one to be preferred. Table 8 shows us that the three-factor model has lower BIC values than the beta factor and two-factor model. So three-factor model seems to better fit than the two others models, for explaining the variation on stock returns.

We also conduct ARCH LM tests in the regression. The classic linear regression model assumes that the variance of the errors is constant. If the variance is not constant then we have heteroskedasticity. An important feature in financial time series is known as “volatility clustering”. Volatility clustering describes the tendency of large changes in asset prices to follow large changes, and small changes to follow small changes, of either sign. So, the level of volatility tends to be positively correlated with its level during the immediately preceding periods.

Engle (1982) proposed a method to discover if the error’s term standard deviation at time *t* depends on squared lagged error term at time *t-1*. According to the test we check if the squared error term is depended on its squared lagged values. Using six lagged error terms, our findings can be seen at Table 10:

ARCH Heteroskedasticity Test (6 lags)						
	B/H	***B/M***	***B/L***	***S/H***	***S/M***	***S/L***
F - Statistic	1.8301	2.4571	5.8564	0.8186	2.252	1.6937
P - Value	0.0999	0.0289	0.0000	0.5578	0.0436	0.1294

Table 10: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011 ARCH Heteroskedasticity Tests: F-Statistic and P-values.

We find strong evidence of ARCH effects in three out of six regressions (S/M portfolio ARCH effect is almost rejected at 5% significance level). So there seems to exist a structure of volatility which is not captured by the Three-Factor model.

Our next step is to estimate the TFM model by using GARCH models. The GARCH model allows the conditional variance to be dependent upon squared lagged error terms and its previous own lags. The GARCH (p ,q) model equation for conditional variance is :

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i u_{t-i}^2 + \sum_{j=1}^{p} \gamma_j \sigma_{t-j}^2$$

where

σ_t^2 is the conditional variance.

u_{t-i}^2 is the squared lagged error term.

σ_{t-i}^2 is the lagged variance term.

α_0 , α_ι , γ_j are constant term, and error and variance coefficients, respectively.

The stationarity condition for conditional variance is:

$$\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \gamma_j < 1$$

We have to mention that GARCH models are no longer usual linear forms. The OLS method cannot be used for GARCH model estimation. One of the main reasons is that OLS estimates minimize the residual sum of squares. The RSS depends only on the parameters, in the conditional mean equation, and not the conditional variance. The method used here is the maximum likehood estimation process.

We are going to employ GARCH (1, 1), GARCH (1, 2), GARCH (2, 1), and GARCH (2, 2) for TFM to check if the time varying nature of variance can be explained. Results are showed on Appendix 2. The e(-1) and e(-2) are the estimates for squared lagged error coefficients u_{t-1}^2 and u_{t-2}^2 , respectively. Also var(-1) and var(-2) are coefficient estimates of σ_{t-1}^2 and σ_{t-2}^2 , respectively. Also the (*), (**), (***) symbols Indicate statistically significant factors at 10%, 5% and 1% level.

We observe that GARCH (1, 2) model results the best estimates according to conditional variance stationarity condition. All coefficients are insignificant at 5% significance level, expect the S/M portfolio. The negative coefficient values of variance equation of S/M portfolio indicate a problem of maximum likehood estimator. Given a set of initial values for the parameter estimates, these values are estimated at each iteration, until it is determined that an optimum is reach. If the likehood function has only one maximum, any optimization method will find it. In the case of GARCH models the likehood function can have many local maxima. So different optimization procedures could lead to different coefficient estimates.

The GARCH (1, 1) model, while gives zero intercepts and beta's close to one, the conditional variance has stationarity problems. We observe that all portfolios expect S/M portfolio, have variance equation coefficients sum more than 1. We get the same results from GARCH (2, 1). Also the GARCH (2, 2) model variance equations for each portfolio seem to explain the volatility in returns, expect the B/H and S/L portfolios.

We can see all coefficient estimates, using all estimation methods, below at Table 11, 12, 13, 14:

	Coefficient *a* estimates					
	B/H	B/M	B/L	S/H	S/M	S/L
White OLS	-0.00094	-0.00798***	0.00174	0.00163	-0.00775***	-0.00106
GARCH (1,1)	0.00110	-0.00445***	0.00200	0.00013	-0.00682***	0.00086
GARCH (1,2)	0.00088	-0.00365***	0.00205	-0.00029	-0.00683***	0.00125
GARCH (2,1)	-0.00001	-0.00490***	0.00270**	-0.00108	-0.00672***	0.00137
GARCH (2,2)	0.00105	-0.00657***	0.00195	-0.00011	-0.00622***	0.00185

Table 11: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011 Intercept coefficient estimates.
(*), (**), (***) Indicate statistically significant factors at 10%, 5% and 1% level.

	Coefficient *b* estimates					
	B/H	B/M	B/L	S/H	S/M	S/L
White OLS	0.92470***	0.88711***	0.96540***	0.98237***	0.85317***	0.94167***
GARCH (1,1)	0.91820***	0.96760***	1.02978***	1.01183***	0.85602***	0.95497***
GARCH (1,2)	0.91386***	0.97726***	1.02991***	1.00924***	0.84529***	0.95458***
GARCH (2,1)	0.92385***	0.95988***	1.03714***	1.00771***	0.85450***	0.95802***
GARCH (2,2)	0.90017***	0.94345***	1.02756***	1.01526***	0.84922***	0.95451***

Table 12: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Market factor (beta) coefficient estimates.
(*), (**), (***) Indicate statistically significant factors at 10%, 5% and 1% level.

	Coefficient *s* estimates					
	B/H	B/M	B/L	S/H	S/M	S/L
White OLS	0.05877	0.02902	-0.17313***	0.89557***	0.89162***	1.12746***
GARCH (1,1)	0.12058**	-0.03372	-0.08862***	0.92512***	0.89828***	1.20554***
GARCH (1,2)	0.12415**	-0.03709	-0.08928***	0.91735***	0.86886***	1.18799***
GARCH (2,1)	0.07119	-0.03662	-0.07272***	0.92340***	0.90034***	1.18962***
GARCH (2,2)	0.13194**	-0.04284*	-0.08491***	0.93520***	0.89684***	1.16795***

Table 13: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Size factor coefficient estimates.
(*), (**), (***) Indicate statistically significant factors at 10%, 5% and 1% level.

	Coefficient *h* estimates					
	B/H	B/M	B/L	S/H	S/M	S/L
White OLS	0.72935***	0.11751	-0.19578***	0.69127***	0.34342***	-0.38361***
GARCH (1,1)	0.64562***	0.03033	-0.11274***	0.71534***	0.33654***	-0.45239***
GARCH (1,2)	0.64502***	0.01953	-0.11351***	0.72745***	0.33650***	-0.45209***
GARCH (2,1)	0.67094***	0.03272	-0.13269***	0.72099***	0.33647***	-0.44713***
GARCH (2,2)	0.66180***	0.09125*	-0.11326***	0.71555***	0.34413***	-0.41193***

Table 14: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011
Book-to-market factor coefficient estimates.
(*), (**), (***) Indicate statistically significant factors at 10%, 5% and 1% level.

Table 11 shows results from coefficient estimates, using OLS, White heteroskedasticity-consistent standard errors & covariance OLS and GARCH models. We observe that all estimation methods result insignificant intercepts expect from B/M and S/M portfolios, which indicate that abnormal returns may exist at medium book-to-market equity portfolios. Only GARCH (1, 1) model give insignificant intercepts, but only for 1% significance level, while GARCH (1, 2) model has B/M portfolio intercept insignificant at 5% significance level.

Table 12 contains estimates of market risk factor, known as beta. We see that all estimation methods resulted significant beta values. We also observe that most estimates are close to one (with the exception of S/M portfolio where beta factor is close to 0.85 in average). This result agrees with capital asset pricing theory, according to which market portfolio capture most of the returns variation.

The next two tables (Table 13 and Table 14) contain the estimates of SMB and HML portfolio coefficients. The size factor SMB seems to play an important role at explaining the variation of returns for most of the portfolios, while using any estimation method. We observe that the small size portfolios have significant coefficient values, which are equal with 0.90 on average. As for big size portfolios we observe that the B/M portfolio has statistically insignificant size factor coefficient according to all estimation methods. Also the size factor is insignificant at 1% level using OLS and GARCH (2, 1) estimation method while is insignificant at 10% level using GARCH (1, 2) and GARCH (2, 2) methods. The B/L portfolio has negative size coefficient, significant at all levels. Those results agree with Fama and French, who show that small size firms have better risk adjusted returns than big size firms. The Table 14 presents coefficient estimates for BE/ME ratio risk factor. Our results are again consistent with Fama and French. We notice that moving from low to high BE/ME ratio firms the value factor coefficient estimates increase, whatever estimation method we use. So according to Fama and French we found also that value firms have better risk adjusted results than growth firms. We also have to mention that value factor does not seem to have explanatory power for B/M portfolio returns, according to all estimation methods, expect GARCH (2, 2) model. Also the value factor is not significant for S/L portfolio returns according to GARCH (1, 1) model.

The Schwarz Information Criteria results are shown Table 15:

	Schwarz Information Criteria					
	B/H	B/M	B/L	S/H	S/M	S/L
GARCH(1,1)	-3.90347	-4.66771	-5.49282	-5.46232	-4.54609	-4.01542
GARCH(1,2)	-3.85964	-4.62993	-5.45330	-5.44407	-4.59347	-3.98049
GARCH(2,1)	-3.71748	-4.64416	-5.62439	-5.43882	-4.50760	-3.96199
GARCH(2,2)	-3.83097	-4.57307	-5.42562	-5.41517	-4.54201	-3.91332

Table 15: Portfolios formed on size and BE/ME: Greece, July 2001 – June 2011 Schwarz Information Criteria values.

According to S.I.C, GARCH (1, 1) is the best estimating model for most portfolios, expect the B/L portfolio.

Another diagnostic test involving the simple OLS method is checking for residual autocorrelation. Using Breusch-Godfrey LM tests we find autocorrelation in the residuals of B/L and S/H regressions, starting at the second lag. As a consequence of autocorrelation in the B/L and S/H regressions, the coefficient estimates are not BLUE even asymptotically. Also autocorrelation may be the cause of the extremely high R^2 of B/L and S/H regressions. This is because the existence of autocorrelation inflates R^2 values for positively correlated residuals.

In addition, we perform normality tests for the residuals. We find that, in every regression, residuals depart from normal distribution. There is excess kurtosis and positive or negative skewness in all six series of residuals. The Jarque-Berra test confirms departure from normality.

Our next test involves checking for multicollinearity between our variables. The facts that we did not face an error message in the econometric software (EViews) provide us evidence that multicollinearity does not exist. Also we constructed SMB and HML portfolio risk factors as zero investment mimicking portfolios. The way they are structured does not allow strong linear relationship between them.

Finally, we perform Ramsey's RESET test to check for misspecification of the functional form of the model. Evidence of misspecification would result rejection of the Three-Factor model. We find that in three of the six portfolios, B/M, S/H and S/M there is misspecification when we add third term to B/M and S/M, and second to S/M. This could be another indication of the existence of nonlinearities in the functional form.

6. Conclusion

In this thesis we investigate the robustness of Fama and French Three-Factor model. We test the TFM model on the Greek stock market for the period June 2001 to June 2011 and it was made on 229 stocks. The TFM explain better the common variation in the stock returns than the capital asset pricing model. Adding HML and SMB portfolio returns to the market excess return as explanatory variables of stock returns gives better results (for slopes and R^2). Moreover, intercepts of stock portfolio regressions on Market, HML and SMB, which are close to zero say that the three factor model explains the cross-section of average stock returns. Results revealed that investors who hold big stocks seem to have higher returns than investors who hold small stocks, so there is a big firm effect. Also investors have higher returns for investing at value stocks than to growth stocks. These results come in line with the findings of Fama and French for the U.S stock market. However, we didn't found statistically significant factors for all portfolios, which question the power of the model.

There are many signs about the validity of the results. Residual distributions are far from normal and we also find signs of residual autocorrelation. Also residual terms are heteroskedastic and ARCH patterns do exist. This led us to construct GARCH models to estimate the coefficient values. The GARCH models resulted better coefficient estimates, solving heteroskesticity and autocorrelation problems. Coefficient estimates from GARCH models agree with those of linear regression models and are consistent with theory. This is evidence that a structure of volatility might exists in TFM. Also misspecification of the model is highly possible, according to Ramsey RESET test.

Another problem is that we assumed that time series come from a single stochastic process. However, the major events that have happened during the sample period (world economic crisis at 2008) may have caused changes in structural relations between variables. In order to address this problem, we must test parameter stability over time. We can conduct a Chow test to compare the parameters of sub-sample periods. It can help us find whether parameters are stable.

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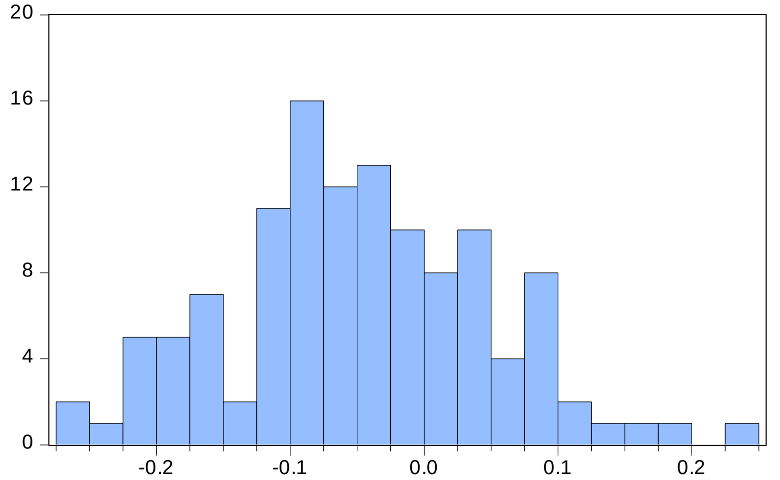
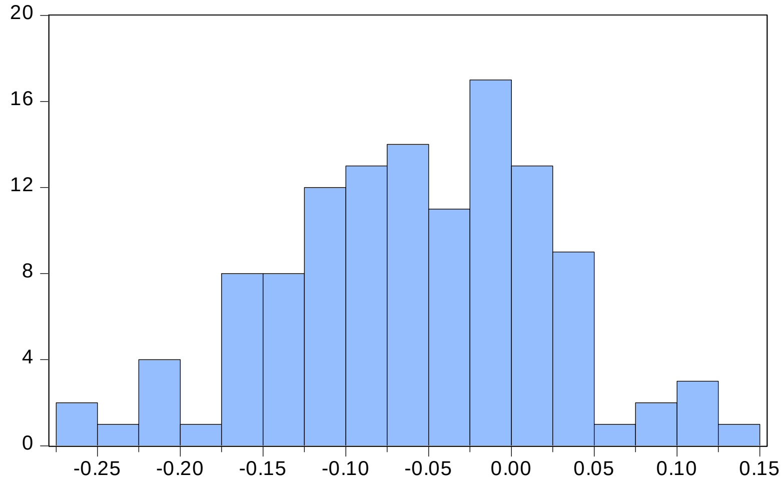
Appendix 1: Portfolios Normality Tests.



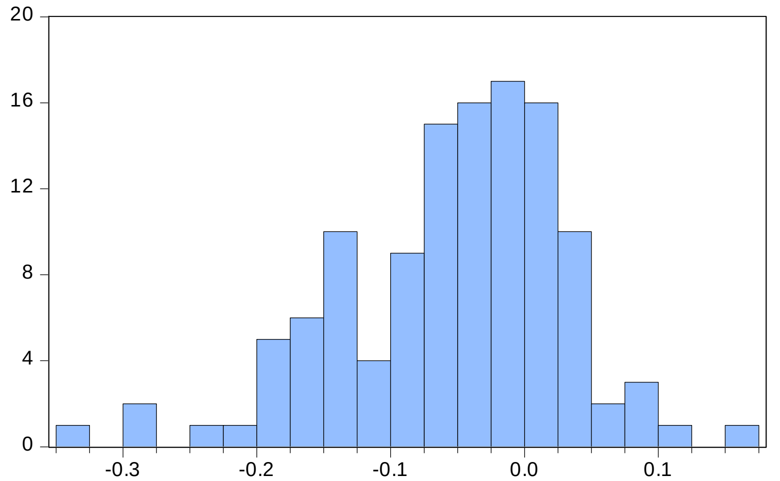
Series: B_H Portfolio
Sample 2001M06 2011M05
Observations 120

Mean	-0.048711
Median	-0.054335
Maximum	0.235904
Minimum	-0.263719
Std. Dev.	0.097754
Skewness	0.154046
Kurtosis	2.898706
Jarque-Bera	0.525904
Probability	0.768779



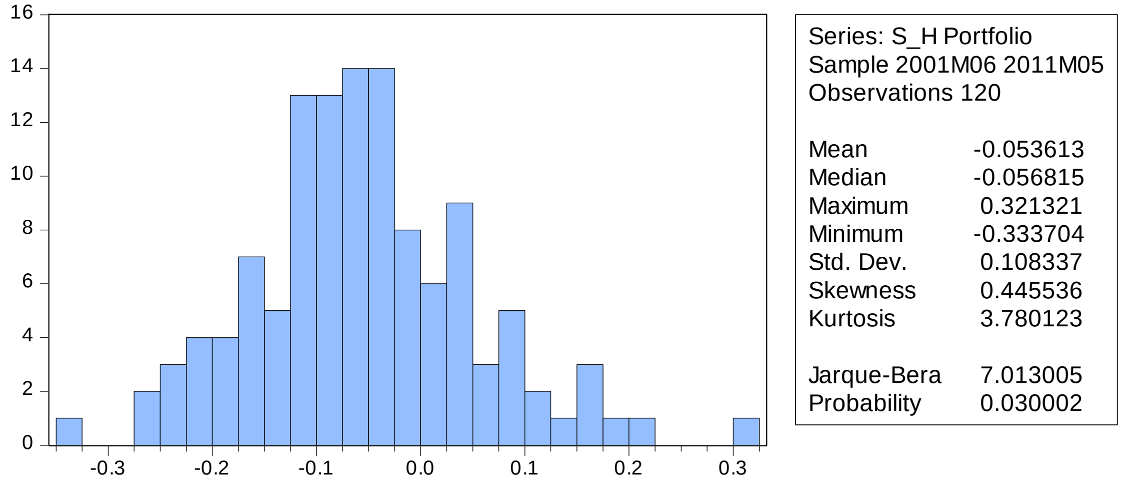
Series: B_M Portfolio
Sample 2001M06 2011M05
Observations 120

Mean	-0.057352
Median	-0.054988
Maximum	0.140733
Minimum	-0.255500
Std. Dev.	0.081047
Skewness	-0.107704
Kurtosis	2.880309
Jarque-Bera	0.303632
Probability	0.859146



Series: B_L Portfolio
Sample 2001M06 2011M05
Observations 120

Mean	-0.053066
Median	-0.039182
Maximum	0.166185
Minimum	-0.345012
Std. Dev.	0.084711
Skewness	-0.685281
Kurtosis	3.900830
Jarque-Bera	13.44967
Probability	0.001201



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-0.3
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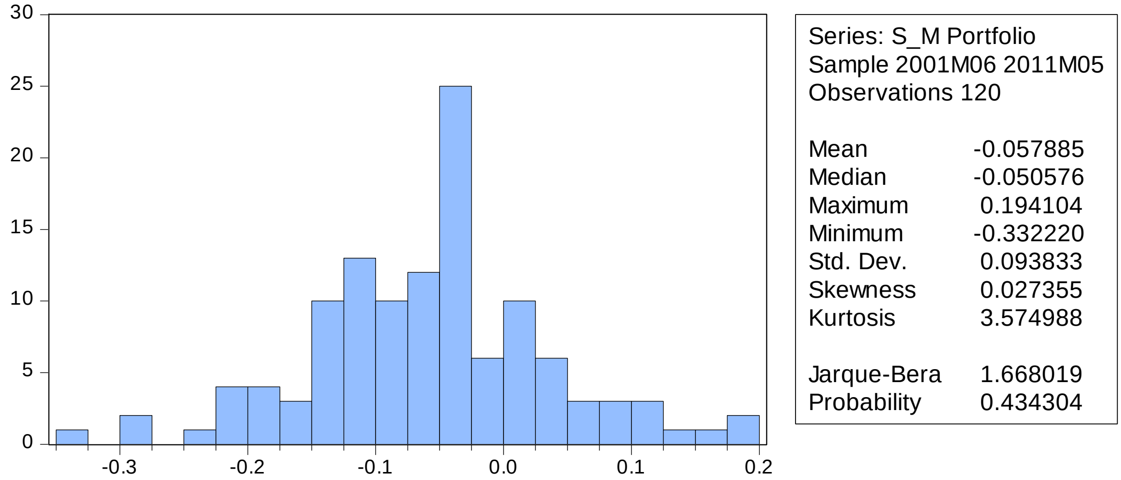
Series: S_H Portfolio
Sample 2001M06 2011M05
Observations 120
Mean -0.053613
Median -0.056815
Maximum 0.321321
Minimum -0.333704
Std. Dev. 0.108337
Skewness 0.445536
Kurtosis 3.780123
Jarque-Bera 7.013005
Probability 0.030002



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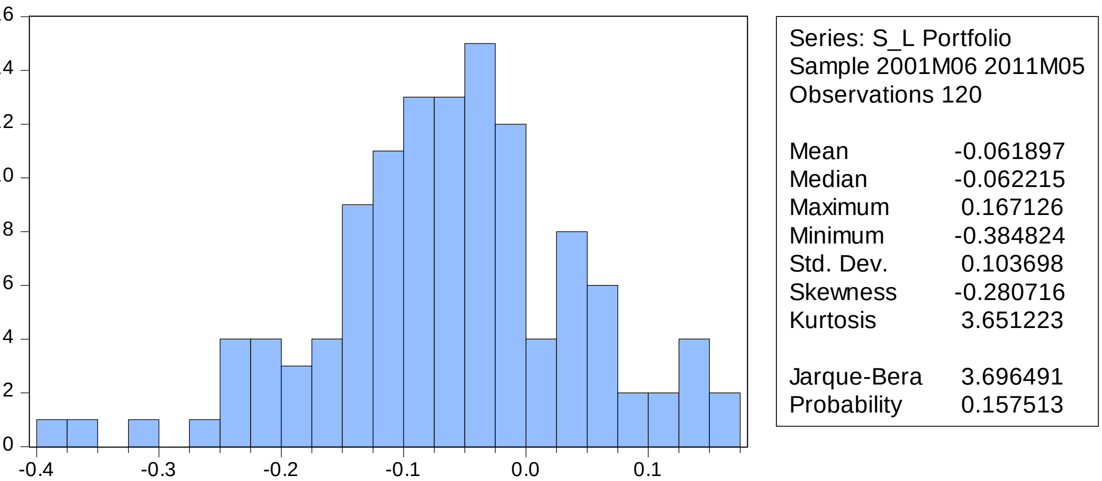
-0.2
-0.1
0.0
0.1
0.2
Series: S_M Portfolio
Sample 2001M06 2011M05
Observations 120
Mean -0.057885
Median -0.050576
Maximum 0.194104
Minimum -0.332220
Std. Dev. 0.093833
Skewness 0.027355
Kurtosis 3.574988
Jarque-Bera 1.668019
Probability 0.434304



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-0.2
-0.1
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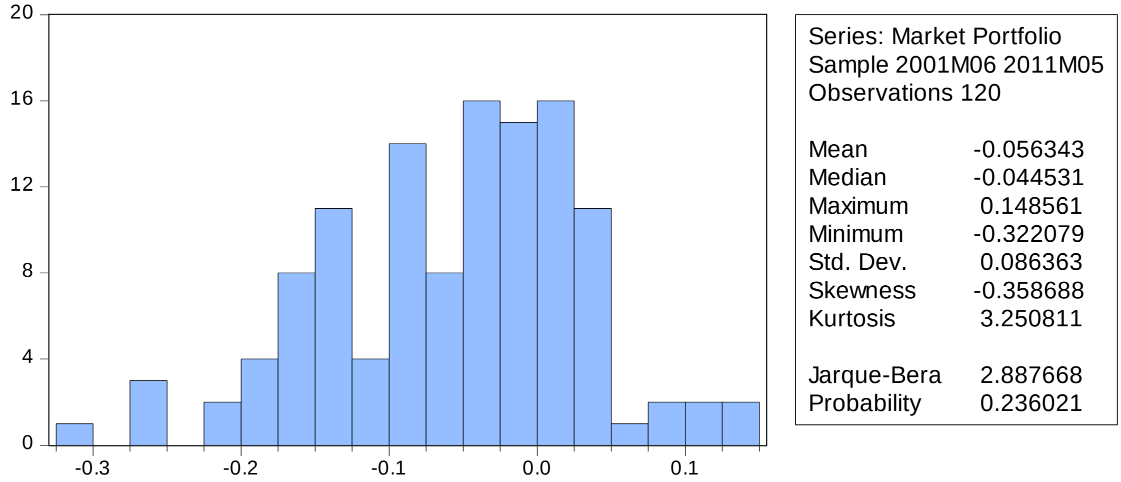
Series: S_L Portfolio
Sample 2001M06 2011M05
Observations 120
Mean -0.061897
Median -0.062215
Maximum 0.167126
Minimum -0.384824
Std. Dev. 0.103698
Skewness -0.280716
Kurtosis 3.651223
Jarque-Bera 3.696491
Probability 0.157513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Sample 2001M06 2011M05
Observations 120
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Median -0.044531
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Minimum -0.322079
Std. Dev. 0.086363
Skewness -0.358688
Kurtosis 3.250811
Jarque-Bera 2.887668
Probability 0.236021
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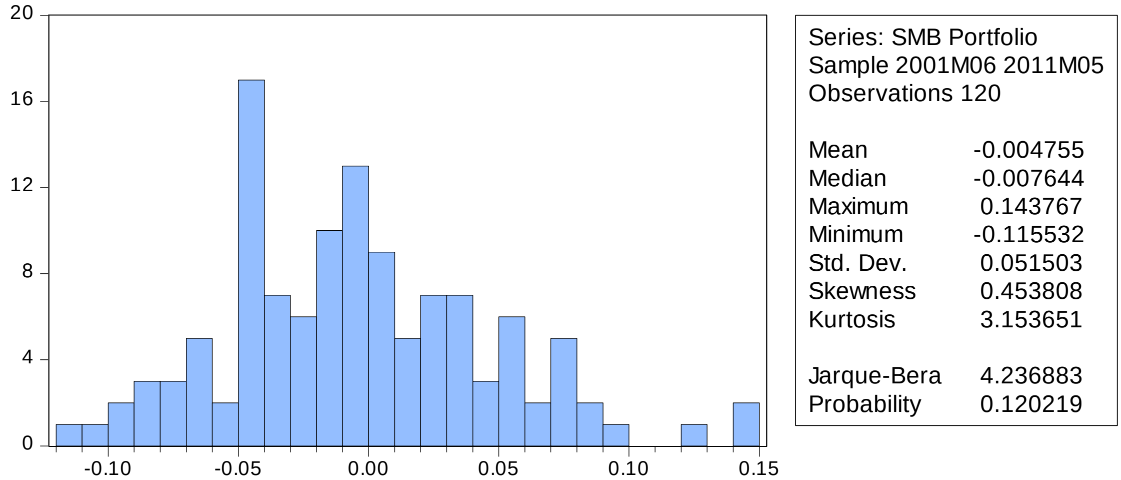
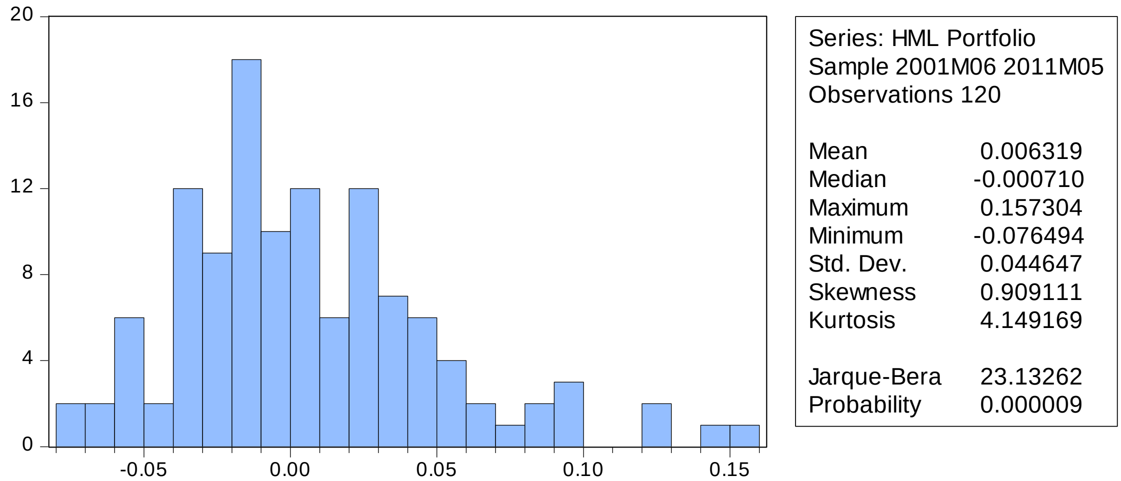
-0.1
0.0
0.1


Series: SMB Portfolio
Sample 2001M06 2011M05
Observations 120
Mean -0.004755
Median -0.007644
Maximum 0.143767
Minimum -0.115532
Std. Dev. 0.051503
Skewness 0.453808
Kurtosis 3.153651
Jarque-Bera 4.236883
Probability 0.120219
20
16
12
8
4
0
-0.10
-0.05
0.00
0.05
0.10
0.15


Series: HML Portfolio
Sample 2001M06 2011M05
Observations 120
Mean 0.006319
Median -0.000710
Maximum 0.157304
Minimum -0.076494
Std. Dev. 0.044647
Skewness 0.909111
Kurtosis 4.149169
Jarque-Bera 23.13262
Probability 0.000009
20
16
12
8
4
0
-0.05
0.00
0.05
0.10
0.15

Appendix 2: GARCH models estimation

	GARCH (1,1)					
	B/H	B/M	B/L	S/H	S/M	S/L
a	0.00110*	-0.00445***	0.00200*	0.00013*	-0.00682***	0.00086*
b	0.91820	0.96760	1.02978	1.01183	0.85602	0.95497
s	0.12058	-0.03372*	-0.08862	0.92512	0.89828	1.20554
h	0.64562	0.03033*	-0.11274	0.71534	0.33654	-0.45239*
	Variance Equation					
c	0.00000	0.00000*	0.00001**	0.00002	0.00042*	0.00001*
e(-1)	-0.05629*	-0.05629*	0.20352**	-0.12607	0.18486*	-0.06704**
var(-1)	1.07018	1.07018	0.70702	1.02114	-0.05454*	1.08056

(*), (**), (***) Indicate statistically insignificant factors at 10%, 5% and 1% level.

	GARCH (1,2)					
	B/H	B/M	B/L	S/H	S/M	S/L
a	0.00088*	-0.00365**	0.00205*	-0.00029*	-0.00683	0.00125*
b	0.91386	0.97726	1.02991	1.00924	0.84529	0.95458
s	0.12415***	-0.03709*	-0.08928	0.91735	0.86886	1.18799
h	0.64502	0.01953*	-0.11351	0.72745	0.33650	-0.45209
	Variance Equation					
c	0.00000*	0.00000*	0.00001*	0.00001*	0.00104	0.00001*
e(-1)	-0.05901*	-0.08646*	0.18883*	-0.14288*	0.12263	-0.05817*
var(-1)	0.93197*	0.61946*	0.64426*	1.06680**	-0.35624	1.24938*
var(-2)	0.14619*	0.51099*	0.07309*	-0.02317*	-0.84231	-0.17968*

(*), (**), (***) Indicate statistically insignificant factors at 10%, 5% and 1% level.

	GARCH (2,1)					
	B/H	B/M	B/L	S/H	S/M	S/L
a	-0.00001*	-0.00490	0.00270	-0.00108*	-0.00672***	0.00137*
b	0.92385	0.95988	1.03714	1.00771	0.85450	0.95802
s	0.07119*	-0.03662*	-0.07272	0.92340	0.90034	1.18962
h	0.67094	0.03272*	-0.13269	0.72099	0.33647	-0.44713
	Variance Equation					
c	0.00013*	0.00000*	0.00000	0.00001	0.00032*	0.00001*
e(-1)	-0.00231*	0.07687*	0.09378*	-0.10456*	0.19184*	-0.02163*
e(-2)	0.14230*	-0.16144*	-0.19717*	-0.03448*	-0.08243*	-0.03900*
var(-1)	0.76009	1.09720	1.03834	1.04014	0.22537*	1.07074

(*), (**), (***) Indicate statistically insignificant factors at 10%, 5% and 1% level.

	GARCH (2,2)					
	B/H	B/M	B/L	S/H	S/M	S/L
a	0.00105*	-0.00657	0.00195*	-0.00011*	-0.00622***	0.00185*
b	0.90017	0.94345	1.02756	1.01526	0.84922	0.95451
s	0.13194***	-0.04284*	-0.08491	0.93520	0.89684	1.16795
h	0.66180	0.09125	-0.11326	0.71555	0.34413	-0.41193
	Variance Equation					
c	0.00001*	0.00000*	0.00003***	0.00002*	0.00088*	0.00001*
e(-1)	-0.06329***	0.17582*	0.27818**	-0.10557*	0.24742*	0.10820*
e(-2)	-0.02488*	-0.26625**	0.37263***	-0.09905*	0.16015*	-0.15361*
var(-1)	0.08938*	0.57458*	-0.13791	0.63350*	-0.73178*	1.37667
var(-2)	1.02092	0.54150*	0.33395**	0.43835*	-0.52402*	-0.32603*

(*), (**), (***) Indicate statistically insignificant factors at 10%, 5% and 1% level.