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DISSERTATION

THE EXISTENCE AND BEHAVIOUR OF STYLE ANOMALIES IN THE GLOBAL EQUITY MARKET:

A UNIVARIATE AND MULTIVARIATE ANALYSIS

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THE EXISTENCE AND BEHAVIOUR OF STYLE ANOMALIES IN THE GLOBAL EQUITY MARKET:

A UNIVARIATE AND MULTIVARIATE ANALYSIS

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Prepared under the supervision of Professor Paul van Rensburg and presented to the Department of Finance and Tax at the University of Cape Town in partial fulfillment of the requirements for the award of the degree of

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ABSTRACT

Style anomalies comprise patterns and relationships found in the cross-section of stock returns data, which contradict the existing asset-pricing models. They have proven to be reasonably effective at explaining the return-generating process of ordinary shares, and have broad uses within modern finance. Empirically, style anomalies are found to have statistically significant rewards in individual markets and small market groupings, and are found to be significant at a sector level on a global scale, but have not been tested at a firm level on a global scale.

The aim of this study is to explain the cross-section of returns of the 1468 largest global firms by market capitalisation. The worldwide study considers stocks from 53 different countries and 112 industries, and investigates the end of month return forecasting power of 44 different firm-specific attributes over the period August 2003 to August 2013. A univariate analysis is performed through a cross-sectional regression of the forward stock returns on the firm-specific attributes in a similar method to Fama and MacBeth (1973). A 'Full Data' regression is also conducted, and results are presented both before and after a beta-adjustment for market risk. Following this, a multivariate analysis is conducted and a forward stepwise procedure is used to construct a multi-factor model.

According to the results of this study, style anomalies exist and have a statistically significant reward at a firm level on a global scale. In a univariate setting there are 25 firm-specific style factors that have a significant return payoff at a 5% level of significance. The specific style groups containing significant firm-specific attributes are the Value, Growth, Momentum, Size and Liquidity, Leverage, and Emerging Market groupings. Ten attributes within these style groupings are found to be robust as they are highly significant both before and after beta-adjustment, and within both a univariate and multivariate setting, namely: EBITDA to Share Price (EBP), Emerging Market (EM), CAPEX to Sales (CXS), Sales to Total Assets (STA), Payout Ratio (PR), 24-month growth in Turnover by Volume (TVO24), Sales to Share Price (SP), 6-month growth in Earnings (E6), 1-month prior return (MOM1), and 3-month prior return (MOM3). This confirms that style effects exist both independently, in a univariate setting, and in a multi-factor model.

The results of this study show that the Value and Emerging Market styles have the highest cumulative payoffs over the 10-year period, and the evidence of strong correlation between attributes within specific styles gives further validation to the traditional style groupings. The behaviour of, and relationships between the firm-specific style factors give great insight into the payoffs to investing in different style factors over time, and are key to the construction of a multi-factor model. The fifteen firm-specific style factors that are significant in a multivariate setting form the core of a multi-factor style model, which can potentially be used to explain a degree of unexplained returns, predict returns, give insight into global market behaviour, and price global assets for use within a global portfolio. These firm-specific attributes include: EBITDA to Share Price (EBP), Emerging Market (EM), CAPEX to Sales (CXS), Sales to Total Assets (STA), Payout Ratio (PR), 24-month growth in Turnover by Volume (TVO24), Sales to Share Price (SP), 6-month growth in Earnings (E6), 1-month prior return (MOM1), 3-month prior return (MOM3), the natural log of Enterprise Value (LNEV), Interest Cover before Tax (ITBT), 6-month prior return (MOM6), Price-to-Book value (PTB), and Cash Flow-to-Price (CFP).

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Introduction

"Ninety percent of what passes for brilliance, or incompetence, in investing is the ebb and flow of investment style."

- Jeremy Grantham

1.1. Introduction

The derivation of an effective asset-pricing model has been fundamental to the study of finance for several decades. Despite the substantial amount of theoretical and empirical work that has been developed over the years, academics and practitioners have yet to agree on a singular model. The theories behind these models are couched in the assumption that market participants are rational utility optimizers, so the models struggle to capture the actual behaviour of stock prices. There have been numerous and persistent patterns in stock returns documented, which contradict the existing asset-pricing models. These so-called 'style anomalies' have proved to be reasonably effective at explaining the return-generating process of ordinary shares.

Styles are essentially groupings of similar firm characteristics that are usually accompanied by similar financial and economic developments. The testing of the existence of the various styles gained momentum after the Fama and French (1992) study strongly rejected the Capital Asset Pricing Model (CAPM) as a result of the existence of size and value effects. With the addition of the momentum, growth, leverage, and January effects, styles have become well researched and well documented within individual markets. While there are many opinions as to whether these anomalies disprove the fundamental finance theories and models, what remains clear is the empirical evidence that style anomalies exist.

The anomalous style effects have broad uses within modern finance. Style variables are seen as a key element to asset allocation strategies and are therefore key to modern portfolio management. They have proven to be successful in asset pricing research in explaining the cross-section of returns, and are used as factors when analysing risk. In recent years, style analysis techniques have been used in performance analysis, attribution and evaluation. It has even become increasingly popular for asset managers to use style anomalies as the basis of their investment strategies, and portfolios constructed to exploit these anomalies are dubbed style portfolios. Style classification, style investing and style analysis are all branches of modern finance stemming from these style anomalies, and highlight the popularity and recent acclaim from the academic and practitioner communities alike.

At this point, very little work has been done to investigate whether these style anomalies exist at a global level, and an assessment of the benefits to style-based investing on a worldwide basis could prove empirically useful. As a result, the primary aim of this study is to reveal whether firm-specific attributes are able to explain the cross-section of returns in a worldwide setting. An analysis of the behaviour of the style factor payoffs over time, and the construction of a multi-factor model will add to the overall understanding of global style effects and the global market in general

Section 1.2 reviews the motivation for this research, Section 1.3 discusses the contribution to literature as well as the objectives of this study, Section 1.4 expresses the formal statements of hypothesis, and Section 1.5 outlines the thesis organisation.

1.2. Motivation for this research

Style anomalies have caused a stir since they were first discovered to be a contradiction to the well-documented CAPM and efficient market theories. Empirical evidence suggests that it is possible to explain returns and price stocks using style factors, rather than the single market *Beta*. This has led to the ultimate quest of improving on the single factor and multi-factor asset pricing models by constructing an asset-pricing model that fully explains stock returns and can be approved and used by academics and practitioners alike. The other side of this coin is in the potential exploitation of these style anomalies in order to devise arbitrage strategies and earn abnormal profits.

Empirical literature has found that these firm-specific factors, more specifically known as style effects, have the ability to explain and predict returns with greater accuracy than the general market *Beta* in different countries, markets, sectors and stocks. However, the magnitude and behaviour of these style effects differs across markets and even across market sectors. To date, style anomalies have never been tested at an individual stock level on a global scale.

With advances in technology, the increasing global presence of companies, and the development of independent markets throughout the world, the notions of a global equity market and international diversification have gained momentum. A great deal of debate has developed in recent literature as to the level of integration within the global financial markets, the fluctuating levels of correlation in bull and bear markets, and effectively the benefits of international diversification. Global investment portfolio management is shown to be a complex extension of domestic fund management, and there are many factors that must be explicitly considered, like currencies, cultural differences, investor preferences, market efficiency, security analysis, and the degree of integration or segmentation of the individual markets around the globe.

Grinold, Rudd, and Stefek (1989) observe that some countries are more segmented than others, and that some factors influence assets across countries while others are influential only within countries. This implies that in a completely integrated global market, returns could be modelled in terms of a global portfolio through one asset-pricing model. However, in a more segmented global market, global returns would have to be modelled in terms of numerous country-specific portfolios. Therefore the development of one general global asset-pricing model to explain, structure and model worldwide asset returns will be challenging to construct, relies on a significant level of global integration, but, in the end will be greatly beneficial to all global investors.

This research takes empirical style findings further through an investigation of the existence and behaviour of firm-specific style anomalies on a global scale. The existence of style factors can lead to the development of asset-pricing models, which can lead to a globally accepted model for understanding, structuring and predicting returns for a global portfolio of shares. An understanding of global asset returns, and the nature and volatility of global factors, is crucial from an academic understanding of global markets, as well as for any international managers' quantitative application decisions such as asset allocation, portfolio risk measurement, and optimization, and is ultimately crucial for managers to earn abnormal profits on a global scale.

1.3. Contribution and Objectives

The chief contributions of this study to the existing literature fall in the categories of the existence and behaviour of global style anomalies, international style-based investing at a firm level, understanding the global market, market efficiency, and the effectiveness of asset-pricing models. This study builds on the thinking of van Rensburg and Robertson (2003), who investigated style characteristics and conducted a very similar study on a cross-section of returns on the Johannesburg Stock Exchange (JSE) and found that six factors represent individually significant effects, all of which support a two-factor model in a multivariate setting.

Modern studies of style anomalies at a global scale were conducted by Acres (2007), Hsieh and Hodnett (2011), and Hsieh and Hodnett (2012a). They all tested for the existence and behaviour of sector-specific style attributes on a global sample of sector returns. Acres (2007) used International Classification Benchmark (ICB) sector returns from 48 different countries, while Hsieh and Hodnett (2011; 2012a) used the Dow Jones (DJ) Sector Titans Composite Index, which only provides exposure to the largest 30 international firms from each of the 19 sectors defined by the ICB. This study of 1468 stocks from 53 countries and 112 different sectors will therefore be by far the largest to date, and will also look at firm-specific factors as opposed to the sector specific factors of the aforementioned studies.

This study aims to empirically investigate whether firm-specific style anomalies exist on a global scale, qualify the identity of the style factors, and examine their behaviour and ability to explain global stock market share returns. The derivation of a suitable multi-factor style-characteristic-based expected return model will be derived, and can be used to better understand the global market, explore the relationship between style factors in a multivariate setting, and forecast global share return. The model can be a useful tool in active portfolio management, asset allocation, performance analysis, and many other forms of both academic and practical investment finance.

Therefore, the basic objectives for this study are to:

1. Investigate the relationship between global stock returns and firm-specific attributes, both before and after risk adjustment.

2. Investigate the univariate behaviour of the payoffs to the firm-specific attributes in terms of consistency and significance, varying market conditions, and robustness to varying time periods.

3. Derive a multi-factor forecasting model. The existence of significant and persistent style characteristics has value beyond the mere disproval of the CAPM, as they can be used as proxies for unobservable risk, and in this way can be included in asset pricing models.

4. Investigate the behaviour of the payoffs to the firm-specific attributes within a multivariate setting, where only the most robust factors retain significance.

5. Test the level of global market efficiency, specifically the weak-form efficient market hypothesis. If firm-specific factors have explanatory power or forecasting ability, this shows either a misspecification of the asset-pricing model, or an inefficient market, or both.

6. Enhance the existing empirical literature by testing previously untested firm-specific factors on a previously untested sample of 1468 global stocks; and extending factor testing beyond those style factors found to be significant in prior research, therefore not only adding to evidence on existing factors but also considering the possibility of other attributes also having explanatory value.

1.4. Formal Statements of the Hypotheses

A two-tailed significance test will be conducted for each of the hypotheses listed below, in order to determine whether the null hypothesis in each instance can be rejected, taking the form:

$$H_0 : |t| < 1{,}96$$
$$H_1 : |t| >= 1{,}96$$

Hypothesis 1: Style effects are significant at a 5% level on a global scale.

Hypothesis 2: Any predictability of asset returns using their style characteristics is not due to risk and does not dissipate after adjustment for risk.

Hypothesis 3: The payoffs to style anomalies are robust to varying time periods and recessionary period.

Hypothesis 4: The style effects exist independently of each other, and not in a multivariate setting.

Hypothesis 5: Style effects are significant predictors of returns when used in a multi-factor asset-pricing model.

1.5. Thesis Organisation

Chapter Two considers the theories behind style anomalies, specifically information efficiency and the Efficient Market Hypothesis, and asset-pricing theories such as the CAPM and the International CAPM (ICAPM). These theories link directly to the Joint-Hypothesis problem, and are key to understanding the anomalous nature of style effects.

Chapter Three reviews the empirical findings of many academics over the past 50 years who investigate style anomalies on the U.S. market, in both univariate and multivariate settings. The empirical findings from non-U.S. countries are then examined, followed by the findings on a global scale. The various explanations for style anomalies are then investigated, and finally the different strategic uses of style anomalies are reviewed.

Chapter Four examines the data that is required for this study in terms of the global sample of shares that will be used, the adjustments that may need to be made to the data, the returns data, the firm-specific factor data, a descriptive statistics analysis, and potential areas of bias.

Chapter Five discusses the methodology that was used to test the data in order to formulate results and insights. The different methods of univariate testing and risk-adjustment are analysed, and the identification of relationships and behaviour is discussed. A multivariate analysis is then conducted, with multi-factor model testing highlighted.

Chapter Six presents the results from the testing, and responds to the objectives and hypotheses of this study. The payoffs to the various style groups are analysed over the period, the univariate and multivariate analysis are compared, and a multi-factor model is constructed.

Chapter Seven summarises and draws conclusions as to the existence of style anomalies in the global market, the behaviour of the univariate factors over time, the significance of the style factors in a multivariate setting, and the formation of a multi-factor return prediction model. Further areas for research pertaining to this topic are suggested.

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Theoretical Overview

"One can say that efficiency must be tested conditional on an asset-pricing model or that asset-pricing models are tested conditional on efficiency "

Fama (1991; p1589)

2.1. Introduction

Before we can examine style, it is necessary to consider the academic theory that has had the most influence on modern investment practice: information efficiency and asset pricing theory. This is directly linked to security valuations and return predictability, which have been the main areas of focus for both practitioners and academics in the field of investment finance for many years. Substantial research has gone into developing and testing models that endeavor to value securities and assess the performance of shares. These asset-pricing models all make the assumption of market efficiency, the idea that asset prices reflect all available and relevant information fully, and are therefore correctly valued (Fama; 1970).

The matter of style effects stems from the efficient market hypothesis and asset-pricing models, and the empirical finding that 'anomalies' exist when these models are tested. Anomalous results could imply an inefficient market, or an incorrectly specified model, or both, due to the fact that investigations of market efficiency cannot be separated from the tests of asset-pricing models (Fama; 1991). These anomalies are termed 'style' factors and it has been established empirically that style characteristics like size; growth/value; leverage; and momentum can be used to predict future returns to some extent either in their own capacity or by including them as factors in models like the CAPM and APT. Information efficiency and asset-pricing theories form the basis upon which tests can be done to investigate style anomalies empirically, and assess whether these style anomalies are present in a global context.

The theory discussed in this Chapter contextualizes the empirical investigations of the later Chapters. Section 2.2 discusses information efficiency and the Efficient Market Hypothesis, Section 2.3 discusses asset-pricing theories and Section 2.4 summarises and concludes.

2.2. Information Efficiency

The degree of information efficiency in a capital market is the extent to which security prices adjust to new information in order to reflect all available information relating to the security. This concept of a market being "informationally efficient" was formalised by Fama (1970), but has roots as early as Bachelier (1900; p21) who suggests in his '*Theory of* Speculation' that: "the influences which determine the movements of the Stock Exchange are innumerable… events past, present or even anticipated… have repercussions on its course".

In his influential paper on efficient capital markets, Fama (1971; p1575) defines the market efficiency hypothesis as "the simple statement that security prices fully reflect all available information" and explains its advantages as: "a clean benchmark that allows me to sidestep the messy problem of deciding what are reasonable information and trading costs". In his previous paper, Fama (1970) presents the efficient market theory in terms of a 'fair game' model, which implies that all market participants have equal access to the same information so assuming all investors are rational, all securities are priced fairly. In order to explain this notationally, Fama (1970) shows that asset-pricing models, which derive prices based on equilibrium expected rates of return on a stock, can be written as a function of risk, given a full set of information available at the time. This can be expressed as:

$$E\left(P_{i,t+1}\middle|\Phi_t\right) = [1 + E\left(R_{i,t+1}\middle|\Phi_t\right)]P_{i,t} \qquad (2.1)$$

Where:

- E shows an expected value
- $P_{i,t+1}$ shows the price of security *i* at time *t+1*
- $R_{i,t+1}$ shows the percentage rate of return for security *i* during period from *t* to *t+1* calculated as $(P_{i,t+1} - P_{i,t}) / P_{i,t}$
- Φ_t is a symbol for the set of information that is available to investors at time *t*
- $P_{i,t}$ shows the price of security *i* at time *t*

This equation essentially indicates that the expected price of security *i* at time (*t+1*) can be determined as a function of the current price at time (*t*) and the expected return on that security over the period (*t*) to (*t+1*), given the set of information available at time (*t*).

According to Fama (1970), the conditions of market equilibrium state that prices are based on expected returns, and the calculation of these equilibrium expected returns is based on the available information set Φ_t. Therefore, trading strategies based on the information set Φ_t will not yield returns in excess of the equilibrium expected returns. The difference between the actual price and expected price, $x_{i,t+1}$, at time *t+1* represents the excess market value for the stock and can be expressed as::

$$x_{i,t+1} = P_{i,t+1} - E\left(P_{i,t+1} \middle| \Phi_t\right) \tag{2.2}$$

Then, to show that trading strategies based on the information set Φ_t in an efficient market do not yield returns in excess of expected returns, the expected excess market value for security *i* is zero:

$$E\left(\bar{x}_{i,t+1} \middle| \Phi_t\right) = 0 \tag{2.3}$$

This equation implies that current prices in an equilibrium market fully reflect all available information and are appropriate with respect to the risk involved. As Janari (2005; p2:3) notes, "the economic rationale is based on the assumption that there are a large number of competing profit-maximising investors that independently analyse and value securities, and these investors attempt to adjust security prices rapidly to reflect the effect of new information belonging to the shared information set Φ_t".

2.2.1. The Efficient Market Hypothesis

Fama (1970; p388) describes his 'fair game' model, also known as the Efficient Market Hypothesis (EMH), as "the hypothesis that security prices at any point in time fully reflect all available information". However, a market that is completely efficient is near impossible to find because, amongst other reasons, there is insufficient access by market players to non-public information, and over or under reaction to information prevails. Therefore Fama (1970) separates the EMH into three levels of market efficiency, which allows the point at which information efficiency breaks down to be determined. The three forms of the EMH are weak-form, semi-strong-form, and strong-form efficiency.

A market is weak-form efficient if current stock prices fully reflect all available market information such as historical prices, trading volumes, rates of return, and other market-generated information. In a weak-form efficient market, stock prices change at random and historical prices contain no information with regards future price changes. In other words, historical rates of return and other market-generated information should have no observable relationship with future rates of return. Future returns are said to be materialize via a 'random walk'.

A market is semi-strong-form efficient if stock prices adjust rapidly to announcements of all information available to the public, including non-market-generated information such as earnings, dividend announcements, financial statement information and ratios. Therefore in a semi-strong-form efficient market, current stock prices reflect not only all historic price information, as in the weak-form efficient market, but also all public information contained in the published financial reports and announcements.

A market is strong-form efficient if stock prices fully reflect all available information from both public and private sources. As such, investors should not be able to derive above average profits consistently, as this type of efficient market would only include individuals with monopolistic or insider access to price sensitive information.

Fama (1991) later redefines the names and understanding of these three forms of efficiency into "tests for return predictability", "event studies", and "tests for private information". In his revision of the weak-form category specifically, Fama qualifies that the future rates of return should not be predictable based on firm-specific attributes and historical fluctuations in returns, so style anomalies should not be able to predict returns at any level of market efficiency.

Grossman and Stiglitz (1980) remind investors, however, that Fama's (1970) EMH contains overly simplified assumptions in that information is not actually costless, so rational investors are only willing to collect information until the marginal cost of obtaining the information equates with the marginal benefit from the extra information. This implies that stock prices would not actually reflect all available information, but rather the information up to the point where buying more information would yield no further gain. Fama (1991; p1575) agreed that "since there are surely positive information and trading costs, the extreme version of the market efficiency hypothesis is surely false".

2.2.2. International Market Efficiency

The concept of international market efficiency is an extension of the information efficiency hypothesis within individual markets in an effort to describe the level of efficiency on a global scale. In general, global efficiency can be considered in terms of the degree of integration or segmentation. Solnik (2000) explains that a fully integrated world financial market would be deemed informationally efficient because capital would be free to flow across borders at little or no cost, and investors would be able to take advantage of any new information in the world market immediately. On the other hand, a segmented market would be considered informationally inefficient due to numerous obstacles to capital mobility, which results in similar assets being priced differently in different countries. These impediments to mobility, and thus efficiency, include legal restrictions, transaction costs, psychological barriers, duties and taxation, political influences and exchange rate fluctuations. In order to assess the level of global market integration, one would need to form a world market portfolio, which would be tested under the pretense of an asset-pricing model. Again, this brings the joint-hypothesis problem into consideration, as any test of market efficiency is also a test of the asset pricing model used (see Section 2.3.3).

The concept of international market efficiency has a large impact on the potential for a single multi-factor model to predict returns and price assets. In a completely integrated global market, where there is perfect information efficiency, it is possible for returns to be modelled through one asset-pricing model as the same factors will have the same level of influence. However, in a more segmented global market, global returns would have to be modelled in terms of numerous country-specific portfolios, as the factors would have different levels of influence and significance between countries.

2.3. Asset Pricing Theory

Asset pricing theory is very simply based on the positive relationship between risk and return, and links very closely to the efficiency theories and equations described in Section 2.2. Total returns are calculated as the sum of the capital appreciation of a stock and the dividend yield. As described in Section 2.2, the expected price is a function of the expected returns and the current price, given a set of available information. Van Rensburg (2000) explains that investors use the available information to forecast expected returns based on the current price as well as the probability distribution (and therefore risk) of future prices. The current price then adjusts according to the market equilibrium models, which suggest higher risk or investor willingness to bare risk is compensated for by higher expected returns. This is evidence of the very relevant informational efficiency assumption of expected return theories, as the prices adjust based on market expectations, which are based on market information.

Prices also adjust based on market forces such as demand and supply. Assuming all investors have homogenous information and expectations, all investors would desire to hold that asset with the highest expected return. As a result of this demand, the asset price will rise, which will lower its expected return, as the potential growth in price is less. This is repeated until all assets in the equity market share the same equilibrium expected return. However, the existence of an 'equity premium' means that investors cannot be solely concerned with expected returns in selecting their investment portfolios, and need to take the risk element into account.

Risk can be measured by the variance of expected returns, and represents the dispersion of returns around the expected mean. The greater the variance of a stock's returns, the greater the risk of actual returns being significantly different to those predicted by a pricing model. The standard deviation of the expected return, or expected portfolio return, is the formalized measure of this risk. There was no intuitively sound or explicit measure for risk until Markowitz (1952; 1959) developed the basic portfolio model, more commonly known as Modern Portfolio Theory. This theory provides a context for understanding the interactions between risk and reward.

Markowitz introduces the mathematics behind risk diversification, and suggests that investors should select portfolios based on the portfolio's overall risk-return characteristics as opposed to compiling a portfolio from stocks that individually have low risk and high return characteristics. Essentially this means that it is possible to obtain higher returns for the same level of risk by including non-correlated assets in a portfolio. The most important implication of this theory is that investors can use mean-variance analysis in order to construct a diversified portfolio, which is both efficient in that it maximises returns for a given level of risk; and it matches their required level of risk aversion. However, the model makes many strong assumptions, which filter down into all applications and must be consistently considered.

In this context, asset-pricing theory is further reviewed with respect to the CAPM, the joint-hypothesis problem, and the International Capital Asset Pricing Model (ICAPM).

2.3.1. The Capital Asset Pricing Model

Tobin (1958) extended the work of Markowitz (1952) by introducing a risk free asset (r_f) into the theory of asset pricing. This allowed for the leveraging or deleveraging of portfolios depending on an individual investor's risk profile, all the while remaining on the efficient frontier. The expected return on this risk-free asset, by definition, has a standard deviation of zero. This addition of a risk free asset lead to the development of the Capital Asset Pricing Model (CAPM), which is generally attributed to a combination of Sharpe (1964), Lintner (1965), and Mossin (1966).

As the CAPM is an extension of the work of Markowitz (1952), the underlying assumptions of the CAPM are the same as those put forward by Markowitz, with a few additons. Some of the strongest and most notable assumptions are that:

- investors are rational 'Markowitz efficient' investors, and therefore only invest in portfolios that lie on the efficient frontier;
- investors can borrow and lend any quantity of money at the risk-free rate, and pay no transaction fees or taxes;
- investors have homogenous expectations in that they have identical opinions with regards to expected returns and correlations between assets;
- investors have the same single period time horizon and are only concerned with their long-term wealth;
- for the purpose of the model, investments are not bound by size limitations, so there are no restrictions to their proportion in a portfolio;
- neither inflation nor interest rates are subject to change, or changes in inflation are fully anticipated and capital markets are in equilibrium.

In addition to these assumptions, the CAPM is based on the theory that investors have varying degrees of risk aversion and adjust their level of exposure to risk by holding varying amounts of a risk-free asset in combination with the market portfolio. The Markowitz (1952) efficient frontier thus becomes a linear combination of the return on the risk-free asset and the return on the market, as shown by the construction of the Capital Market Line (CML) and the Security Market Line (SML).

The CML graphically simulates the expected return for a portfolio of risky assets as follows:

$$E(r_P) = r_f + \frac{\sigma_P}{\sigma_m}\left[E(r_m) - r_f\right] \tag{2.4}$$

Where:

- $E(r_P)$ shows the expected return on the portfolio of risky assets, *P*
- $E(r_m)$ shows the expected return on the market portfolio, *M*
- r_f shows the risk-free rate of return
- σ_P shows the standard deviation (risk) of the portfolio of risky assets
- σ_m shows the standard deviation (risk) of the market portfolio

In order for portfolio *P* to be efficient, it must be fully diversified so all non-systematic, firm-specific risk is diversified away. The market does not reward investors for non-systematic risk because it can be diversified away in a portfolio. Therefore, when considering individual securities, a different risk measure that only takes systematic risk into account is required. *Beta* is such a risk measure.

Beta represents the asset's covariance with the market, standardised by the expected variance of the market portfolio's return. The *Beta* for a security *i* is defined as:

$$\beta_i = \frac{Cov(r_i, r_m)}{\sigma_m^2} \tag{2.5}$$

Where: $Cov_{i,m} = p_{i,m}\sigma_i\sigma_m$

The SML uses the *Beta* described above to simulate the expected return of an individual risky security *i* as follows:

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] \tag{2.6}$$

In theory when a market is in equilibrium, all individual assets and all portfolios should lie on the SML.

Fama and French (1996; p1947-1948) state: "the main implication of the CAPM is that in a market equilibrium, the value-weight market portfolio, *M*, is mean-variance-efficient. The mean-variance-efficiency of *M* in turn says that:

(i) β, the slope in the regression of a security's return on the market return, is the only risk needed to explain expected return;

(ii) There is positive expected premium for β risk.

Our main point is that evidence of (ii), a positive relation between β and expected return, is support for the CAPM only if (i) also holds, that is, only if β suffices to explain expected return."

This is the most important implication of the CAPM: the idea that the only relevant factor that should be taken into account when pricing an asset; given the expected market return, return variance and risk-free rate; is the asset's covariance with the market (*Beta*). However, the CAPM can be seen as limited in its practicality due to its restrictive underlying assumptions and reliance on a theoretical market portfolio; nevertheless, it has a reputation as the first formal asset pricing model of modern finance and is respected as such.

The CAPM model is essentially a model of expected returns, which are *ex ante* (expected) variables. In practice, however, only *ex post* (realised) returns are observable. Therefore, the Single-Index model is used to test the predictive power of the CAPM by comparing the CAPM predicted returns to the observed *ex post* returns.

When using the Single-Index model, two further assumptions need to be made beyond the CAPM assumptions:

- An appropriate index can be found that perfectly represents the unobservable market portfolio.
- Stock returns are stationary over time.

The Single-Index model can be expressed as:

$$(r_i - r_{f,t}) = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \varepsilon_i \qquad (2.7)$$

Where:

- r_i shows the observed realised return on asset i at time *t*
- $r_{m,t}$ shows the observed realised return on the market index at time *t*
- $r_{f,t}$ shows the risk-free rate of return at time *t*
- α_i is the regression intercept which shows the unexplained excess systematic return on asset *i* (abnormal returns)
- β_i is the regression coefficient which shows the sensitivity of the excess return on asset i to the excess return on the market
- ε_i is the unexplained residual return (standard error) on asset i at time t

Any deviations from this theoretical CAPM framework are termed 'anomalies', and are revealed by a significant intercept in the regression output above (α). This implies that there are significant abnormal profits available to the investor, which is in stark contrast to the CAPM, which predicts the alpha to be zero.

It must be noted that the CAPM needs to be evaluated based on the validity of its predictions, as well as the basis of its assumptions. Style effects are examples of anomalies that exist when testing the CAPM, so while it is uncertain whether the assumptions or the model itself is responsible for the existence of anomalies, this study will still add to the literature that questions the effectiveness of the CAPM and endeavors to create an improved asset-pricing model on a global scale.

2.3.2. The Joint-hypothesis Problem

As explained in Section 2.2, an efficient market is one in which the expected returns implied by the current price of the stock should reflect the risk of the stock. However, in order to examine efficiency in any given market, an asset-pricing model is needed to quantify the expected return generation. The CAPM, as described in Section 2.3.1, is one such model, and as a result, the joint efficient market hypothesis has arisen. Asset pricing models are fundamentally inseparable from the consideration of market efficiency.

That being said, in order to empirically test the accuracy of the CAPM it is necessary to construct a theoretical market portfolio. While many broad equity indices can be used as proxies for a market index, they fail to account for the fact that a market portfolio is not only limited to equities but includes both tradable and non-tradable assets too. Therefore empirical tests of the CAPM become tests not only of the pricing model but also of the efficiency of the underlying index proxy. Unless the market portfolio can be known with certainty, the CAPM can never be tested accurately.

The existence of style anomalies is inconsistent with the predictions of both efficient markets and the asset pricing models as they provide investors with the ability to predict the movement of share prices to some extent. Anomalous explanatory variables aren't supposed to exist in efficient markets using the CAPM as a risk-return model.

2.3.3. The International Capital Asset Pricing Model (ICAPM)

The ICAPM extends the domestic CAPM to a global context in which investors have different geographical locations and markets, use different currencies, and have different consumption preferences. One of the most noteworthy differences is that the market risk factor is no longer a domestic market risk, but rather a global market risk. This extension of market risk means that additional terms are required in order to capture the asset's covariance with the various global exchange rates. The international investor needs to be compensated for additional currency risk that cannot be diversified away fully because currency movements affect all stocks in the portfolio to some extent.

Dumas and Solnik (1995; p445) suggest that asset-pricing models should price the exchange rate risk because "investors of different countries face different prices of goods at which they consume the income from their investments". Essentially this is a result of deviations in purchasing-power-parity (PPP). As Dumas and Solnik (1995; p445) explain: "stochastic changes in exchange rates are associated with changes in these prices and constitute additional sources of risk in asset pricing models." They suggest that an asset-pricing model should include risk premia, derived from the covariance of the stocks with exchange rates, in addition to the traditional *Beta* risk premium, which is derived from the covariance with the market portfolio.

Dumas and Solnik (1995) show that a CAPM incorporating a foreign-exchange risk premium is better able to explain the structure of global returns than is the classic CAPM. The ICAPM expected return on asset *i* can be expressed as follows:

$$E(r_i) = r_f + \beta_i\left[E\left(r_g\right) - r_f\right] + \sum_{n=1}^{N} \gamma_{i,n} E(r_n) \tag{2.8}$$

Where:

- $E(r_i)$ shows the expected return on asset i
- $E(r_g)$ shows the expected return on the global market portfolio, *G*
- $E(r_n)$ shows the expected return on the foreign currency of country *n* relative to the US Dollar
- r_f shows the U.S. risk-free rate of return
- β_i shows the sensitivity of the expected return on asset i to the expected excess return on the global market
- $\Upsilon_{i,n}$ shows the sensitivity of the expected return on asset i to the expected return on the foreign currency of country *n*

Dumas and Solnik (1995) test their version of an international asset-pricing model, the International CAPM, against the normal CAPM, and find that under circumstances of "exact PPP and no barriers to international investment", the normal CAPM holds. However, in normal circumstances, their tests on the stocks and currencies of the world's largest markets emphasise the need for a foreign exchange risk premium. They explain that foreign exchange risks are vital contributors to the explanation of stock returns in the international financial market, and that the international CAPM is better than the original CAPM.

Like the domestic CAPM, the ICAPM is subject to the same inherent weaknesses in that it also relies on a hypothetical market portfolio that cannot be observed. It is even more difficult to find a proxy for the international model, as this proxy would need to capture the entire universe of internationally tradable and non-tradable assets.

2.4. Summary and Conclusion

This Chapter gives a theoretical overview of market information efficiency and asset pricing theories in order to put the empirical investigations and tests in later Chapters into context.

Market efficiency and asset pricing theories are inextricably linked, inferring that any test of asset pricing is immediately a test of market efficiency. This leads to the joint hypothesis problem as a failed test could imply a poor asset pricing model, or an inefficient market, or both. Any asset-pricing or information efficiency conclusions will be made within the joint hypothesis context.

Mean-variance analysis and portfolio selection are the foundations upon which the CAPM is developed, along with a set of assumptions consistent with mean-variance optimization. The CAPM suggests that all investors will hold a portfolio comprising a combination of the market portfolio and a risk-free asset, with relative weights depending on the investor's level of risk aversion. The standard domestic CAPM is then extended to allow for international factors and results in the ICAPM, which models expected return in a global economy and takes foreign currency risk into account.

It must be noted that the existence of style anomalies is inconsistent with the predictions of both the efficient market and asset pricing models as it allows for the forecasting of returns to some extent. These efficiency and asset-pricing theories are comprehensively reviewed in the following Chapter, which discusses empirical findings on style anomalies.

- 3 -

Literature Review

"There is mounting evidence that relative stock returns can be predicted by factors that are inconsistent with the accepted paradigms of modern finance."

Haugen and Baker (1996; p401)

3.1. Introduction

The literature on information efficiency, asset-pricing theories and anomalous factors is extensive, and conflicting empirical evidence has been put forward by numerous academics on the matter. It is clear, however, that there is continued interest in explaining stock market returns and testing asset-pricing anomalies. This Chapter endeavors to deliver a balanced analysis of the most prominent and relevant literature, and highlights important contributions made by various authors over the past few decades.

Style effects had particular attention drawn to them as a result of the contentious Fama and French (1992) study, however evidence that the cross-section of stock returns can be explained by numerous style variables abounds in pre-1990 literature. These style variables include the size effect; value effects (including price-earnings, market-to-book, and dividend yield ratios), the growth effect, the momentum effect; the leverage effect; and the January effect. In more recent literature it appears there is greater interest in interpreting these anomalies, and creating and testing new asset-pricing models using the anomalies as explanatory factors, as opposed to investigating their existence in individual markets. However, as style anomalies have never been directly tested at a firm-specific level on a global scale, the focus of this research will be twofold: the existence of style effects as well as the interpretations and modeling of these findings.

Style effects have been well documented in the United States, but they exist in other markets around the world too. This Chapter will therefore analyse the empirical findings for the existence of style anomalies, the interpretation of these style anomalies, as well as the use of those findings in investment strategies both in the U.S. and abroad, as well as the world in general. Given the vast amount of literature available, only the more pertinent findings are reviewed.

Section 3.2 gives a brief review of the U.S. findings, Section 3.3 reviews the findings from non-U.S. countries, Section 3.4 reviews the global findings around style anomalies, Section 3.5 attempts to interpret the anomalies, Section 3.6 discusses the strategic use of style anomalies, and Section 3.7 summarises and concludes.

3.2. Review of U.S. findings

The Capital Asset Pricing Model (CAPM), described in Section 2.3.1, has molded the way academics and practitioners think about risk and returns for many years. Assuming the market is efficient, the CAPM implies that the expected returns on securities are a positive linear function of their market *Beta*s, and the market *Beta*s are adequate to describe the cross-section of expected returns.

The empirical findings of Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) both support the CAPM as they show a positive relationship between average stock returns and *Beta* for the pre-1969 period. In addition, Fama and MacBeth (1973) find that *Beta* is the only measure of risk that affects expected returns, that there is on average a positive tradeoff between risk and return, and that the behaviour of returns over time supports the existence of an efficient market. However, more recent tests like those of Reinganum (1981), Lakonishok and Shapiro (1986), and Fama and French (1992) find that the positive simple relationship between *Beta* and average returns vanishes during the more recent 1941-1990 period. Therefore their findings do not support the most basic prediction of the CAPM as the average stock returns are found to not be positively related to market *Beta*s.

There are many more empirical contradictions of the CAPM, almost all of which are grouped as style anomalies. These style anomalies are often able to partially explain the discrepancy in average excess returns, even after being adjusted for risk by an asset-pricing model. They essentially take into account a portion of the unexplained variation that the asset-pricing model doesn’t account for. Many factors have been distinguished for their ability to explain the cross-section of excess returns successfully, either by themselves, or in combination with other factors. The empirical findings from the United States are analysed as follows.

The most prominent style factor in early studies is the size effect, which was first documented by Banz (1981) who tests the effect of firm size, while controlling for systematic risk, on New York Stock Exchange (NYSE) stock returns over the 1927 to 1975 period. Banz finds that market capitalization, a stock's price multiplied by the number of shares outstanding, provides additional explanatory power to the market *Beta* when analysing the cross-section of average returns. The average returns on stocks with relatively smaller market capitalisation are higher than one would expect based on their *Beta* estimates, and they tend to outperform stocks with relatively larger market capitalisation, which have lower average returns than expected based on their *Beta* estimates. Banz queries the stability of the size effect over time, however, and suggests a lack of theoretical foundation. Roll (1981) argues that this apparent size effect is a result of the thin trading of small stocks relative to large stocks which causes a downward bias in the *Beta* estimates of returns.

After the size effect was documented, Bhandari (1988) identified the leverage effect after finding a positive relationship between leverage and average return. It is logical for leverage to be associated with increased risk and expected return, but in the traditional CAPM, leverage risk should be captured by the market *Beta*. However, Bhandari finds that a leverage factor assists in the explanation of the cross-section of average stock returns, even when size and *Beta* factors are included in the tests.

The dividend yield effect, one of the primary value factors, was also investigated several decades ago. Litzenberger and Ramaswamy (1979) consider the effect of tax and the dividend yield on NYSE data from 1936 to 1977 and find a strong positive relationship between the dividend yield and the before tax expected return on common stocks. This finding was supported by Blume (1980), who finds a similar dividend yield effect for the period from 1946 to 1976. Keim (1985) considers NYSE common stock data from 1931 to 1978 and finds that a factor related to dividends influences share returns even after accounting for the varying tax treatments of dividends and capital gains. Fama and French (1988) test the 1927 to 1986 period on the NYSE for a dividend yield effect and find that in the short run (one to three months), the dividend yield typically explains less than five percent of the variation in share returns, however, in the long run (two to four years), the dividend yield is far more significant and explains in excess of 25 percent of the variation.

Another primary value factor, the earnings yield, was also tested and discovered many years ago. Basu (1977) used data from the period 1957 to 1971 to test whether the price-to-earnings (P/E) ratio has significant explanatory power for U.S. stock returns. Using a low P/E ratio as an indication of high value stocks, Basu finds that stocks with relatively lower P/E ratios tend to outperform stocks with higher P/E ratios, even on a risk-adjusted basis. Ball (1978) proposes that the P/E ratio is an all-encompassing alternative for unidentified factors in expected returns. It can be understood economically that shares with higher risks and expected returns would have lower prices relative to earnings, irrespective of the unidentified sources of risk. However, Reinganum (1981) found that over the 5 year period form 1970 to 1975, the P/E factor was not significant after controlling for the size factor, which implies that the two factors must be linked in some way and may be proxies for the same set of unknown missing factors. Basu's (1983) more recent results contradict Reinganum's (1981) findings when he reveals that P/E ratios "help to explain the cross-section of average returns on U.S. stocks in tests that also include size and market *Beta* factors". These studies all emphasize the importance not only of the existence of these style factors, but of the correlations between factors, as they have a potentially significant impact on the successful exploitation of a given style effect.

In line with this same value effect, Rosenberg, Reid, and Lanstein (1985) find a positive relationship between average returns on U.S. stocks, and the ratio of a firm's book value of equity to its market value of equity (BE/ME). Rosenberg, et al. also find that stocks with high BE/ME tend to outperform the market. This BE/ME is also seen as a determinant of value as firms with high book-to-market values are seen as value stocks. This implies that the stock is essentially underpriced as it contains a lot more intrinsic value that isn't being priced by the market. An additional value factor was identified by Chan, Hamao and Lakonishok (1991) as stocks with a high ratio of cash-flow to price (CF/P) forecast higher returns. This is expanded upon by Lakonishok, Shleifer and Vishny (1994) who investigate the BE/ME, CF/P, price-to-earnings ratio and historic growth in sales over the period from 1963 to 1990, and find that value stocks can be classified as having relatively higher BE/ME, higher CF/P, lower price-to-earnings ratios and lower historic growth in sales, and that value stocks outperform expensive non-value stocks.

Keim (1988) incorporated all of the style effects mentioned above and found that price-earnings, size, leverage, and book-to-market value can be used as factors in an analysis of stock prices and returns in order to obtain insight into risk and expected return behaviour. Keim also noted that P/E, size, leverage, and BE/ME are all "scaled versions of price", so it is reasonable to expect that some of the factors are superfluous when describing average returns.

In an introduction to the momentum effect, Bernard and Thomas (1990) found that there are medium-to-long-term inertia patterns in stock returns. They found that stocks that have performed well in the previous six to twelve months have good future prospects, and vice versa. In response to this finding, Jegadeesh and Titman (1993) use a momentum investor strategy in which they buy past 'winners' and sell past 'losers' in the period from 1965 to 1989 in the U.S. They base their zero-cost winner and loser portfolios on the previous six months returns and find that they both earn significant returns when held for a period of six months. It therefore seems medium-term momentum has a positive relationship with returns, and is able to explain a portion of unexplained returns deviation. In addition, Jegadeesh and Titman (1992) found evidence of a short-term momentum effect, which involves a negative relationship between returns and one-month prior returns. This can be seen as a form mean reversion, or compensation for overreaction in the market.

Fama and French (1992) test the cross-section of average stock returns in the 1963 to 1990 period. They find that the individual relationships between average stock return and each of the size, leverage, P/E, and BE/ME factors are different to the simple relationship between *Beta* and average returns. They conduct multivariate tests, which show that the negative relationship between size and average stock return and the positive relation between BE/ME and average stock return are robust and persist in combination with other variables. Fama and French (1992) also find that the combination of size and book-to-market equity seems to absorb the effects of leverage and P/E in average stock returns during the sample period. Irrespective of the underlying economic causes, their main contribution is that two style variables, size and BE/ME, provide a simple yet robust classification of the cross-section of average stock returns.

Fama and French (1993) later build on this empirical finding and propose a 3-factor asset-pricing model incorporating both size and value premia, in addition to the CAPM market risk premium. This is one of the first models developed specifically to utilise style anomalies in asset pricing. The premium for size risk is calculated as the small capitalisation stock returns minus the large capitalisation stock returns, and the premium for value risk is seen as the excess return to the portfolio of stocks with high book-to-market ratios, relative to the portfolio of stocks with low book-to-market ratio. Fama and French (1993) find that this three-factor model is significantly better able to explains the returns to the style portfolio than is the CAPM. Brennan et al. (1998) test the Fama and French (1993) three-factor model and conclude in agreement with the model that both size and book-to-market characteristics explain return deviations, however they add that the Fama and French three-factor model is unable to explain the momentum effect. Conversely, Carhart (1997) uses monthly return reversals, both short and long term, as a momentum factor which is added to the Fama and French three-factor model to form the Carhart (1997) 4-factor model, which successfully captures the momentum style anomaly on the U.S. stock market.

Haugen and Baker (1996) examine over fifty potential factors on the Russell 3000 stock index in the U.S. in an effort to determine whether the five style factor groupings: risk, liquidity, price, growth potential, and momentum in prices, have significant explanatory power over expected stock returns. They discover the existence of common factors that have significant ability to determine the relative expected returns among different stocks. Haugen and Baker (1996) find evidence (a) of a short-term reversal and medium-to-long-term inertia pattern in the returns history; (b) that the value variables (BE/ME, P/E, CF/P) all exhibit positive payoffs and are important to the cross-section explanation; (c) that the market price over current cash flows ratio (MP/CF) has explanatory power, as higher expected returns are usually associated with companies that have a high level of profitability; and (d) of the liquidity effect, as stocks with high and growing levels of trading volume tend to be priced so as to yield lower levels of expected return. Their results appear to be consistent with the hypothesis that the U.S. market is made up of investors who use very similar determinants of differences in expected return, all of which are based on style factors.

3.3. Review of non-US findings

While it is clear that style anomalies exist to varying degrees in the United States market, it is also necessary to examine the magnitude and persistence of these style anomalies in different countries around the world, as it could be possible that these effects are sample specific to the

U.S. financial market. In general, samples from non-U.S. countries are much smaller due to factors such as: the limited number of listed stocks in comparison to the U.S., the fact that many international equity markets have not been active for as long as ones in the U.S., and the fact that many non-U.S. countries have only recently modernized their financial system. Another possible difficulty is the thin trading problems that many non-U.S. financial markets experience, especially emerging markets, which can lead to biases in computed returns and mismeasurement of risk parameters and correlations.

One of the first studies to produce evidence of style anomalies outside of the U.S. was done by Chan, Hamao, and Lakonishok (1991), who find convincing evidence that book-to-market equity is a significant factor when explaining the cross-section of average returns on Japanese stocks. Heston, Rouwenhorst, and Wessels (1999) later tested for the size effect in many industrialized European markets, while Chen and Zhang (1998) tested for style anomalies in the financial markets of South-East Asia. Together their results show that out of the thirteen developed equity markets tested, the size effect is positive in eleven of them, but is it statistically larger than zero in only four. While this evidence for the size effect may seem weak, the size effect is significant in both the U.K. and Japan, the two countries with the largest capitalization of listed stocks after the U.S. Leledakis and Davidson (2001) further expand that the size effect persists in the U.K. even after controlling for the book-to-market ratio. Fama and French (2006), however, show that after adjusting for the value premium, the size effect is relatively weak in the developed world.

Rouwenhorst (1999) conducts tests in the emerging markets and finds much stronger evidence of the size premium, however he does not adjust for the value effect, which could mean his tests compromise validity. Findings by Van Rensburg and Robertson (2003) reveal the characteristic variables of dividend yield, cash flow-to-price, price-to-earnings, price-to-profit, price-to-NAV, and size are all able to contribute significantly to the explanation of the cross-section of Johannesburg Securities Exchange (JSE) returns in the South African market. They also derive a two-factor asset-pricing model, incorporating the style variables of size and price-to-earnings as explanatory variables.

Drew and Veeraraghavan (2002) tested whether premia for value and size risks are present in Malaysian stocks. For the period under review from 1993 to 1999 it was found that both the value and size risk effects are present and significant. Drew and Veeraraghavan (2003) expanded on these findings to test the power of the Fama and French (1993) 3-factor model for pricing South-East Asian stocks in Hong Kong, Korea, Malaysia and the Philippines. They find that the Fama and French (1993) 3-factor model explains more of the South-East Asian stock returns than does the market model.

Further testing of emerging economies was conducted by Serra (2002), who finds that significant style factors are common across emerging economies, and are similar to the factors identified as significant within the developed markets; specifically 3-month momentum, earnings yield, dividend yield, book-to-market. Serra (2002) also finds, in contradiction to evidence from the developed economies, that the average payoff to size and liquidity factors is positive and therefore the size effect is not supported in emerging markets.

Gaunt (2004) researched the explanatory power of the Fama and French (1993) 3-factor model on the Australian Securities Exchange (ASX) over the period from 1981 to 2000, and finds that the 3-factor model is significantly better than the CAPM over the testing period. Janari (2005) examines the existence and behaviour of style characteristics on the ASX over the June 1994 to May 2004 period, and confirms the existence of many uncorrelated anomalies from which he develops a five-factor style model for the ASX.

It is therefore clear that style effects exist in different countries, to differing degrees, and over different periods, but their individual power and their interaction with each other remain points of contention. This makes it even more interesting when investigating groups of countries, and more specifically the biggest group of countries possible - the global market. Empirical studies on worldwide data will be reviewed in the following Section.

3.4. Review of Global Findings

While it is clear that style anomalies persist in the U.S. and other countries individually, to the author's knowledge there have been no studies conducted on whether style anomalies exist at a firm-specific level on a global scale. What has been found, however, is that the Fama and French (1993) 3-factor model, which uses the size and value factors in addition to the traditional *Beta*, generally improves the explanatory power of the CAPM significantly in international studies. This is based on tests done on a small group of countries or sectors internationally.

Haugen and Baker (1996) tested whether style anomalies exist in Japan, France, the United Kingdom, Germany, and the U.S. over the period 1985 to 1994. They find that: (a) there is a high degree of similarity in the significant factors that explain differences in expected returns; (b) the direction of the average payoffs are the same in all five tested countries; and (c) the same factors seem to affect expected returns in all five countries as all of the factors are significant at high levels of probability. They also find that as a result of international diversification, they were able to lower returns volatility, while enhancing the spread in realised return, when compared to the capitalization-weighted five-country equity index. Haugen and Baker (1996) conclude that style effects are significant and unexpectedly stable over time, with evidence across multiple time periods and multiple markets.

Michaud (1999) considers the same five markets as Haugen and Baker (1996), namely France, Germany, Japan, the United Kingdom and the United States over the period from 1990 to 1997. He investigates the seven style factors: asset yield, cyclicality, earnings trend, earnings yield, normalised earnings yield, return reversal and size, and finds that the level of significance of the factors seems to vary depending on the market, however the earnings trend and return reversal are significant in all markets. This is contrary to the findings of Haugen and Baker (1996) and implies that significant style factors seem to vary between markets, so strict style-based investment may be unsuccessful on a global basis.

Maroney and Protopapadakis (2002) endeavored to “explain the effects of the book-to-market ratio and market capitalization using a stochastic discount factor (SDF) model on international stocks in Australia, Canada, Germany, France, Japan, the United Kingdom and the U.S.”. Their findings reveal that the value and size effects persist under the SDF model when tested on this international sample. The value and size effect seem to have a significant presence on a global scale.

Acres (2007) tests for anomalous attributes in sector returns using the International Classification Benchmark (ICB) sector index returns, in a worldwide study of 48 developed and emerging countries. He finds that (a) market indices cluster into developed and emerging markets indicating a benefit to market diversification; (b) traditional asset-pricing models do not adequately capture the return-generating process in worldwide sector indices; and (c) attributes exist in three style groups: the 'value', 'growth' and 'momentum' groups. However, these sector-specific attributes suffer from a lack of consistency.

Research into global sector-specific style effects was continued by Hsieh and Hodnett (2011) who examine the existence and behaviour of empirical style anomalies within each of the global equity sectors. They find the book-to-market ratio (value effect) and market capitalization (size effect) to have significant bearing on the pricing of sector returns over the period from 1999 to 2009 within a univariate setting. Hsieh and Hodnett (2012a) extended their research to test whether the Fama and French (1993) 3-factor model has the ability to explain the variations in the global sector returns. They find that, under a 3-factor model, abnormal returns can be found in both the industrial and information technology sectors, however, the previously abnormal returns to the resource sector fall away under the 3-factor model. In addition, they find that the most significant contributor to abnormal returns in the model is the market risk premium. They find further that the payoff direction and significance of value and size factor exposures are not uniform across all sectors. This finding is contrary to most empirical studies on style portfolios, and suggests that a global style investment strategy cannot be successfully applied across market sectors. They therefore conclude that "sector allocation might be more effective in terms of global active portfolio management or international diversification than style allocation and country allocation".

3.5. Interpretations for the CAPM style-based anomalies

Bhandari (1988) shows evidence that a share's estimated sensitivity to the market; *Beta*, does not describe the equilibrium risk-return relationship sufficiently. Jegadeesh (1992) takes it a step further and gives evidence that when portfolios are constructed so that *Beta* and firm-size have low correlation, *Beta* explains virtually none of the cross-sectional variation in returns when compared to size. Fama and French (1992) confirm this finding and expand on it by concluding that the cross-sectional variation in stock returns is as a result of size and book-to-market value factors. Building on this, Fama and French (1993) find that three factors explain the cross-sectional variation in share returns: a market factor, a size factor and a book-to-market value factor. Later, Daniel and Titman (1997) conclude in agreement that both size and book-to-market ratios are highly correlated with average stock returns. These are all examples of the single factor CAPM failing to adequately explain returns and therefore a deviation from the standard CAPM is required in order to account for these 'anomalies'.

There are many explanations for these deviations from the CAPM. The Fama and French (1993) study discussed above implies that style anomalies like a firm's size and book-to-market equity ratio are simply proxies for the loadings on risk factors, which is consistent with the risk model. This was challenged in a subsequent study on U.S. stock returns by Daniel and Titman (1997), who demonstrated using a two-way sorting portfolio methodology that the cross-section of U.S. stock returns cannot be explained solely by loadings on shared risk factors, but rather by the attributes themselves. Daniel, Titman and Wei (2001) extended this investigation to a Japanese sample and ratify that an attribute rather than loading should be used as an explanation of the cross- section of returns.

Chen (1991) is a proponent of the efficient market hypothesis and argues that technical patterns or anomalies are explained by the belief that the risk premiums on stocks are time varying. Haugen and Baker (1996) find that "risk premiums in expected returns become larger (smaller) as the risk of stocks becomes larger (smaller) or as investors' sensitivity to risk grows (declines) and therefore the levels of risk and risk aversion can both change with the business cycle". Both studies therefore suggest that the systematic patterns that are evident in historic stock return data can be the result of time varying risk premia, and as a result have a risk-based explanation that simply requires a more comprehensive *Beta*.

It therefore appears that the explanations for deviations from the CAPM are either risk-based or non-risk-based. The risk-based explanations suggest that the failure of the CAPM is the result of one or many missing risk factors in the model, and is therefore solved by extending the CAPM to a multifactor model. The non risk-based explanations suppose some kind of bias, either in the data, the testing, or the mentality of market participants. The question of the mentality of the market participants is vitally important, which is why Van Rensburg (2001) classifies explanations of the anomalies into three groups: investor irrationality, investor rationality, and methodological bias. Whichever way one looks at it, these anomalies have been prevalent in empirical literature and, although there are many different explanations, the focus of this study is on whether the style anomalies exist on a global scale and not the reasons for their existence. The next Section focuses on the uses of style anomalies.

3.6. Strategic Application of Style Anomalies

From the discussions above it is clear that there are many style factors that have success in explaining the cross-section of excess returns, either in isolation, or in combination with other factors. The existence of these style factors has led to the conclusion that they can be very useful in many different areas of finance. This section centres on the empirical findings that style anomalies can be used in a strategic manner to predict returns, classify stocks, allocate assets, and conduct performance analysis and evaluation. These applications are discussed below, and add to the relevance and necessity of this study.

3.6.1. Predicting Returns

DeBondt and Thaler (1985), Jegadeesh (1990), Chopra, Lakonishok, and Ritter (1992), and Jegadeesh and Titman (1993) demonstrate that the historic returns on a stock assist in the prediction of future returns. In addition, Fama and French (1992) Lakonishok, Shleifer, and Vishny (1994), and Davis (1994) find that future returns can be predicted by factors such as the market capitalization of a stock and the values of accounting ratios, such as book value or earnings per share, in addition to the risk of the stock.

The reaction to this evidence has been strong, since it exhibits contrasting evidence to the information efficiency and asset pricing theories. However, the basic premise of the results still holds, and style factors are documented to assist in the prediction of returns beyond the ability of the relative risk when using asset pricing models in different markets around the world and over different time periods.

3.6.2. Style Classification

Barberis and Shleifer (2003) emphasize that "one of the clearest mechanisms of human thought is classification: the grouping of objects into categories based on some similarity among them". This behaviour is clearly visible in financial markets, where investors typically break down available stock options into asset classes such as government bonds, value stocks and large capitalisation stocks before making portfolio allocation decisions (Bernstein; 1995).

In recent times, many investment professionals have taken to classing assets based on observable style anomalies, which are believed to generate abnormal returns. The popularity that style anomalies and style classification have garnered, has introduced a demand for indices that mirror these investment styles. Today, it is common for even the broadest U.S. stock indices to be broken down into style groups.

3.6.3. 'Style Investing' and Asset Allocation

Barbaris and Shleifer (2003) describe the term 'style investing' as: allocating funds among style-characterised asset classes rather than among individual securities, and is practically achieved by investors categorizing risky assets into different styles, as described above, and moving funds between these styles in response to their relative performance. Style has become integral to many asset allocation strategies and, as such, is a key element of modern portfolio management.

Lakonishok, Shleifer and Vishny (1994) show that a long position in a value portfolio combined with a short position in growth, over a five-year horizon, appears to generate constantly positive profits. They also note that the value strategy significantly outperforms the growth strategy during bullish economic conditions, and continues to outperform even in bearish conditions. These findings are confirmed by Liew and Vassalou (2000), who perform tests on ten industrialized countries and find that the phenomenon of value stocks outperforming growth stocks in bearish economic conditions persists in all but one of the countries under review. This shows that style allocation can have positive effects on portfolio returns regardless of economic conditions.

Daniel and Titman (1999) explore the profitability of an investment strategy that combines value with the momentum effects, but does not consider size effects. They find that a strategy that utilises both of these anomalies can be very lucrative, as purchasing stocks with high momentum and high book-to-market ratios, while selling stocks with low momentum and low book-to-market ratios, yields a negative return in only 3 out of 34 years (9%). In comparison, Fama and French (1996) show than the market return on their three 3-factor model (comprising value, size and risk factors) is negative about 30% of the time.

Hogan et al. (2004) introduce a concept of 'statistical arbitrage', and define it as a trading strategy that costs nothing to initiate and provides a positive expected profit that becomes riskless as the length of the investment horizon approaches infinity. They then find that value strategies based on sales growth and cash-flow-to-price, calculated *ex post*, exhibit statistical arbitrage, but that the evidence of the book-to-market effect is weaker and the size effect does not exhibit statistical arbitrage.

3.6.4. Performance Attribution and Evaluation

Style-based analysis, introduced by Sharpe (1992), is a modern tool for analysing mutual fund returns, and is a popular portfolio performance attribution methodology. Sharpe (1992) proposed style analysis to customize a benchmark for each manager's returns, in order to measure the manager's contribution more exactly. In return-based style analysis, a factor model is used to explain fund returns and is founded on the premise that stock returns can be attributed to the returns of style factors. The inputs to the factor model are the returns on several style-based benchmark portfolios, such as value, growth, size, momentum, country, or sector.

Grinold and Kahn (2000) explain that style analysis results are a top-down attribution of the portfolio returns to style and selection. According to this concept of style analysis, the style holdings define the type of manager, and the selection returns distinguish among managers, so that one is able to use style analysis to identify a manager's style, analyze performance, and analyze associated risk.

Even though there are questions as to the accuracy of style-based performance analysis, it is generally an improvement over the basic returns-based methodologies. It is an excellent tool for large studies of manager performance and as such Barbaris and Shleifer (2003) note that "money managers are now increasingly evaluated relative to a performance benchmark specific to their style, such as a growth or a value index".

3.7. Summary and conclusion

There have been numerous U.S. studies that document anomalous effects in the context of the CAPM and efficient markets, and it has become a stylized fact that anomalous factors are persistent and significant across varying markets. There are many different explanations and applications for these anomalies, yet there is still no consensus as to the true meaning of these anomalies. Some argue that the risk model is inadequate and therefore at fault; others argue that there are forms of bias in the data, methodology or mentality of market participants, which causes markets to be inefficient.

This Chapter introduced the anomalies by reviewing some of the first U.S. studies to discover the particular anomalies. A review was then conducted on non-U.S. studies to show that these style anomalies persist in other countries too, all be it to occasionally lesser degrees. Empirical insight into the existence and significance of global style anomalies was then investigated.

Empirical literature shows that the size effect is persistent, and while statistical issues may affect the magnitude of the size effect, none of the issues is able to completely mitigate the size effect. Earnings-to-price ratios and book-to-market equity ratios are classified as value effects and have been found to be persistent in both the U.S. and global markets. Size effect and book-to-market effects were both used in the Fama and French (1992) three-factor model to explain returns. In this way the size, price-to-earnings and book-to-market value effects have been found to be intrinsically linked and it is suggested that they combine as a proxy for some unidentified risk factor. Leverage, dividend yield, and momentum also provide a simple, yet robust explanation of the cross-section of average stock returns when tested empirically. These style anomalies can be applied not only to returns prediction; style classification; style investing and asset allocation; but also to style analysis, performance attribution and evaluation.

While the actual interpretation and implications of the style anomalies are yet to be formally understood, the existence of these effects in various markets and sectors around the world is certain. No study has yet been done on the global stock market in general, which is why this study is both relevant and progressive. This study adds to the literature on style anomalies as it investigates the greatest number of individual shares from the greatest number of countries ever tested empirically, as prior empirical investigations either focus on sectors-specific factors or simply test a handful of countries.

It may be a while before these style anomalies are completely and universally understood, but the fact remains that these style anomalies have proven to be very useful in identifying systematic risk factors at an academic level and enhancing profitability at a practitioner level, and therefore their existence and behaviour must be tested and documented further.

- 4 -

Data and Descriptive Statistics

"The goal is to transform data into information, and information into insight"

- Carly Fiorina (2004)

4.1. Introduction

This Chapter introduces the data that will be analysed in later Chapters. The data consists of two subsets: stock returns data and firm-specific attribute data. The biases that can exist in financial data are discussed, and various adjustments investigated so as to help reduce the impact of any bias in the sample set. Descriptive statistics are presented for all of the returns and firm-specific factors under consideration.

The *Econometrics Views* (E-Views) statistical software package is used to perform the majority of the analysis conducted in this paper, following the initial data capturing and handling using Microsoft Excel. The monthly data was gathered for the period August 2000 to August 2013, however the analysis was conducted for the period August 2003 to August 2013.

Section 4.2 discusses the global share sample selection, examines the stock returns and firm-specific attribute datasets, and provides details of their construction and the techniques used in sorting and manipulating the data prior to analyses. Areas of potential bias are also deliberated. Section 4.3 presents relevant descriptive statistics and outlines any necessary adjustments. Section 4.4 presents a summary of the datasets and concludes.

4.2. Data

All share price, dividend, and financial statement information required for the returns and firm-specific attribute data was obtained from the *Datastream* database terminal, which was accessed from the Business Corner in The Research Wing at The Chancellor Oppenheimer Library at the University of Cape Town.

A thorough descriptive statistics analysis was completed and any suspect data points or outliers were investigated. *Datastream* automatically adjusts for capital events like rights offers, unbundling of shares and share splits; and additional areas of concern were manually accounted for throughout.

4.2.1. Global Share Selection

The top 1500 global shares based on Market Value are captured in this study. The series represents the highest investable market capitalization stocks across 53 countries, split into two market segments: 'Developed' (26 countries) and 'Emerging' (27 countries). The top 1500 shares provide sufficient exposure to the largest and most liquid international firms from a variety of sectors. This sample is therefore considered an adequate proxy for the global market.

4.2.2. Continuity of Data

The extremely large nature of the dataset required the raw data to be collected over a number of days. Due to the actively traded nature of the stocks under review, this time lapse allowed the Market Values of these firms change constantly with market movements, and as such, the top 1500 shares were not constant on each day that the data was gathered. This allowed for 61 shares to drift in and out of the top 1500 share sample over the period of data capturing.

A process was therefore followed to ensure that the same shares were analysed for the entire period. For the sake of completeness, those shares that either came into the sample or left the sample during the period of data collection, thus leaving incomplete records; were removed from the sample. The 1468 shares that remained are therefore consistent throughout the period.

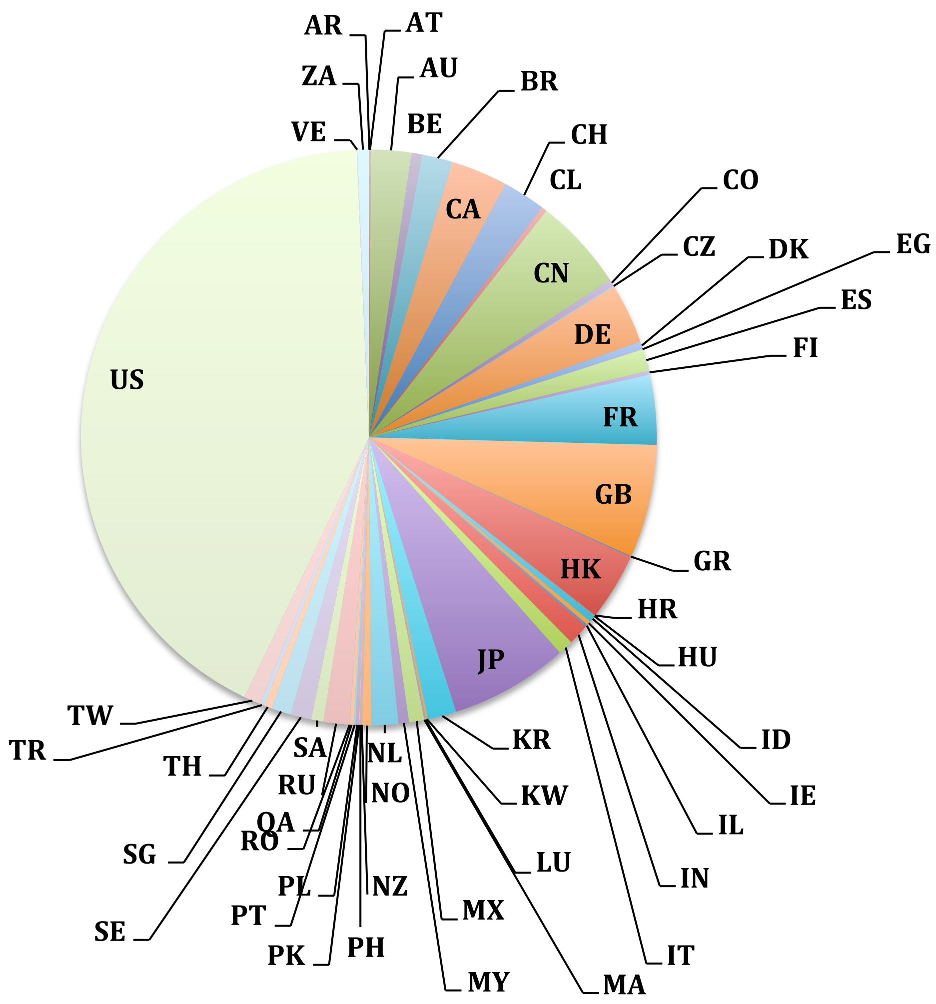
4.2.3. Data Statistics

After smoothing the gathered data, the remaining top 1468 global shares by Market Value are treated as the base dataset on which this analysis is performed, and comprises shares from 53 countries and 112 industries. Due to the nature of the sampling process, these shares represent a cross-section of the top 1468 shares currently in existence and as such, it is the case that not all of these companies listed as of 2013 were around from the beginning of the testing period. As a result, the number of complete data observations in the sample grows as time progresses. Due to the fact that the starting point for the selection of global stocks is chosen at the end of the period, the study is subject to a level of survivorship bias, which will be discussed in the Sections to follow.

Figure 4.1 below gives a visual representation of the different countries that are included in the dataset, proportioned by their Market Value. Table 4.1 shows the different sectors that are included in the dataset, proportioned by their Market Value and Figure 4.2 presents the Market Value distribution of Emerging countries compared to Developed countries.

Figure 4.1: The distribution of stocks in the global top 1468 based on the Market Value of the stocks from each country that are included in the series

There are 53 countries represented in the top 1468 global shares based on Market Value (MV). 27 of these countries are defined as 'Emerging' and 26 are defined as 'Developed'. The most notable countries are the 514 stocks from the US with a MV of \$16.3 trillion, 125 stocks from Japan with a MV of \$2.5 trillion, 71 stocks from Great Britain with a MV of \$2.4 trillion, and 79 stocks from China with a MV of \$2 trillion. A country code key can be found in Appendix A, and the complete figures can be found in Appendix B.



A visual representation of the distribution of stocks in the global top 1468 based on the number of the stocks from each country is shown in Appendix C.

Table 4.1: The equally weighted distribution of stocks on the global top 1468 based on the number and MV of stocks from each sector that are included in the series

There are 112 industries represented in the top 1468 global shares based on Market Value (MV). The 30 largest industries are displayed here. The most notable industries are the 154 stocks from the Banking industry with a MV of $5.4 trillion, 42 stocks from the Integrated Oil and Gas industry with a MV of $2.5 trillion, and 39 stocks from the Pharmaceuticals industry with a MV of $2 trillion. The complete industry list with Market Values can be found in Appendix D.

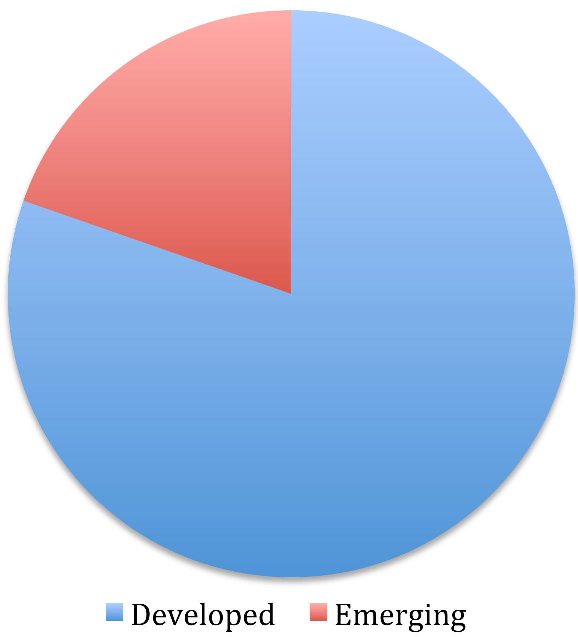
Industry	Number of shares	Value ($ million)	% total MV
Banks	154	**5383209,14**	14%
Integrated Oil & Gas	42	**2533473,39**	7%
Pharmaceuticals	39	**2021537,08**	5%
Mobile Telecom.	42	**1320538,52**	3%
Exploration & Prod.	52	**1061462,22**	3%
Automobiles	25	**934878,76**	2%
Divers. Industrials	23	**853434,85**	2%
Computer Hardware	11	**838346,63**	2%
Fixed Line Telecom.	23	**813467,41**	2%
Broadcast & Entertain	31	**799114,97**	2%
Life Insurance	36	**793469,91**	2%
Software	18	**735402,60**	2%
Food Products	38	**721395,24**	2%
Con. Electricity	43	**706444,62**	2%
Broadline Retailers	15	**669028,44**	2%
Semiconductors	26	**636764,42**	2%
Commodity Chemicals	21	**571566,00**	1%
Tobacco	11	**528797,67**	1%
Internet	9	**514572,77**	1%
Brewers	13	**473322,56**	1%
Real Estate Hold, Dev.	29	**443817,12**	1%
General Mining	10	**443751,41**	1%
Specialty Chemicals	24	**433887,8**	1%
Industrial Machinery	27	**422534,14**	1%
Biotechnology	15	**419869,85**	1%
Investment Companies	2	**418300,59**	1%
Soft Drinks	12	**402237,37**	1%
Clothing & Accessory	17	**395142,42**	1%
Computer Services	12	**391217,43**	1%
Food Retail, Wholesale	25	**377053,02**	1%

It is clear from this analysis that a wide range of sectors are represented in the global sample, which mirrors the vast range of sectors that are present in the global population, and therefore provides an added degree of rigor to the sample selection. In addition to the range of sectors represented in the sample, a second factor which validates the choice of sample is the country-weightings which are present. With the U.S., Japan, China and the U.K. well represented, the chosen sample is a relatively accurate representation of the global market.

A further illustration of the distribution of shares in the global sample, based on their Emerging or Developed nature, is displayed in Figure 4.2. This too is an accurate representation of the Market Value discrepancy in the global market.

Figure 4.2: The distribution of stocks in the global top 1468 based on the Market Value of the stocks from emerging and developed economies

There are 53 countries represented in the top 1468 global shares based on Market Value (MV). Of those 53 countries, 27 countries are defined as 'Emerging' and have a combined MV of $7.6 trillion. The other 26 countries are defined as 'Developed' and have a combined MV of $31 trillion. A complete list of countries and classification criteria can be found in Appendix E.



4.2.4. Stock returns data and adjustments

Data on monthly dividend-adjusted share returns, market capitalization and trading volume was collected for the top 1500 companies for the period August 2000 to August 2013. While the empirical tests are only performed using the period August 2003 to August 2013, the previous returns data was used to compose momentum and growth variables needed for the analysis. The *Datastream Return Index* 'datatype', the core of this analysis, shows a "theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date" (*Datastream*; 2013).

From the initial sample of 1500 shares, preference shares and shares with insufficient total returns observations were removed. The sample was smoothed as discussed in 4.2.2, leaving 1468 shares to be analysed further. The following further adjustments were considered:

4.2.4.1. Completeness

Complete data is a vital component for robust results. All data in this study is subject to the level of completeness of the data on the *Datastream* database. At the same time, it is doubtful whether the companies listed as of July 2013 were all listed throughout the examined period and therefore observations may not exist for certain periods. Haugen and Baker (1996) deal with incomplete stock returns data by assigning the population mean value for each exposure. This treatment opens the sample up to bias, as figures that are missing in the current record may have been available during the period of testing and replacing these values with a population mean could materially impact forecasts. It is however their belief that applying a population mean to unavailable information is a more appropriate treatment than simply removing the incomplete stock from the population. Due to the size of this study, the number of observations at any point is statistically significant and therefore allows for some incomplete periods of data. The incomplete data points were therefore left blank so as not to bias the results.

4.2.4.2. Comparability

The returns data for the 1468 stocks needs to be standardised to a uniform currency for comparability purposes, as the stocks operate in different countries and currencies. All monetary, financial and accounting information for each share was therefore converted into U.S. Dollars, using *Datastream*, at the prevailing exchange rate on the relevant historic date. A completely standardised method of conversion was therefore employed.

4.2.4.3. Liquidity

An analysis of the liquidity of the shares, and choice of only liquid and tradable shares is vital for robust results. If shares trade infrequently or even not at all, returns data can be heavily skewed or be non-existent which would impact negatively on the final results. Thin trading would suggest that the price does not necessarily reflect all the available relevant information, so the stock may not be at the correct price level simply because it has not traded in a while. This then leads to the capital gains being calculated incorrectly as the price may not reflect the true value of the share. To add to this, Dimson (1979) notes that non-traded shares have a downward bias in the estimation of covariance with the market, and therefore *Beta* would be underestimated. Robertson (2002) confirms this by explaining that systematic risk; *Beta*, is estimated using a covariance matrix of stock returns and the market return, so it would appear that the prices of non-traded shares do not move with the market.

As an initial test for tradability, it is possible to focus on the shares from one country in order to effectively analyse their liquidity within their specific market. These findings can then be extrapolated to the whole sample, provided the country selected is a good representation of all economies included in the series. An emerging market country was chosen for the liquidity test in order to be prudent in the analysis, as emerging market shares are less likely to be liquid due to the immaturity of the market. In line with these requirements, the South African shares in the sample were tested against the local FTSE/JSE Top 40 Index.

In accordance with the *Ground Rules for the Management of the FTSE/JSE Africa Index Series*, the FTSE/JSE Top 40 Index consists of the "largest 40 companies ranked by full market value (before the application of any investability weightings), in the FTSE/JSE All-Share Index" (FTSE; 2013). The FTSE has many guidelines that are used to create such indices, one of which pertains directly to liquidity: "Securities must be sufficiently liquid to be traded. The following criteria are used to ensure that illiquid securities are excluded:

- Reliable Price: The FTSE/JSE Advisory Committee must be satisfied that an accurate and reliable price exists for the purposes of determining the market value of a company.

- Liquidity: Securities which do not turnover at least 0.5% of their shares in issue, after the application of any free float restrictions, per month in at least ten of the twelve months prior to an annual review in December by the FTSE/JSE Advisory Committee will not be eligible for inclusion in the indices for the next twelve months. (FTSE; 2013)"

The South African shares in the sample are displayed in Table 4.2 with their relative positioning on the FTSE/JSE Top 40 Index. It can be concluded that those listed on the FTSE/JSE Top 40 Index are liquid.

It must be noted that many of the shares included in the FTSE/JSE Top 40 Index are dual-listed and are categorized in this analysis as originating from the non-South African country. These include, with their relative positioning: British American Tobacco (1), SABMiller (2), BHP Billiton (3), Compagnie Financiere Richemont (4), Anglo American (8), and Old Mutual (12).

Table 4.2. South African Shares listed in the FTSE/JSE Top 40 Index

The table below lists the South African shares that are included in the top 1468 series, their position on the FTSE/JSE top 40 as at 15 November 2013, and their market value. While many of the shares in the FTSE/JSE Top 40 Index are dual-listed and therefore not included as specific to South Africa specific in the series, all of the 15 South African shares included in the top 1468 series are well within the top 40 shares of the FTSE/JSE Top 40 Index.

Share Name	Position in FTSE/JSE Top 40 Index	Market Value ($ million)
MTN GROUP	6	34522,92
NASPERS	5	34446,89
SASOL	7	30530,77
STANDARD BK.GP.	9	18089,79
VODACOM GROUP	11	16862,81
FIRSTRAND	10	16554,32
KUMBA IRON ORE	13	14152,77
NEDBANK GROUP	18	13258,7
BARCLAYS AFRICA GROUP	14	11340,86
ANGLO AMERICAN PLATINUM	16	10790,16
ASPEN PHMCR.HDG.	15	10501,87
SANLAM	17	9438,82
SHOPRITE	19	8979,05
REMGRO	20	8784,96
BIDVEST GROUP	21	8089,52

Therefore it is clear that the 15 South African shares are liquid. As the South African shares represent an emerging market, we can extrapolate the finding to the rest of the emerging market shares as well as the developed market shares – which are more liquid by definition due to the maturity of the market. Therefore an initial analysis reveals that the sample of shares is deemed to be liquid.

It must be noted that this liquidity test is conducted at the end of the period. The shares which are deemed liquid now may not have been liquid throughout the period, however due to the size of the companies and shares involved it can be assumed that the shares in the top 1468 series have been traded to some extent throughout the period.

Haugen and Baker (1996) find a 'bid-ask bounce' problem as a result of the thin trading of shares because shares are traded at the bid or ask price, whereas returns are generally measured from close-to-close. This leads to returns appearing to be negatively autocorrelated even when they are not, which would lead to a false conclusion that the previous period return has predictive ability; a false application of the momentum effect.

4.2.4.4. Outliers

Outliers in the data may occur as a result of irregular events or errors in the data source, so the obviously erroneous outliers were removed manually to start. In order to further eliminate the negative effects of outliers, a form of 'winsorisation' procedure was then applied to the returns data. A mean and standard deviation of the returns was calculated across all of the shares for each month. A limit of three standard deviations from the mean was set, and any observations greater than that limit were temporarily excluded from the sample. A new mean and standard deviation was calculated from the remaining observations. The temporarily excluded observations were then added back into the sample, and all of the outliers were reduced to exactly three standard deviations from the new mean. This technique has the advantage of retaining all of the available data points, whilst at the same time ensuring that the regression results were not greatly influenced by outlying observations. Finally, a manual check of the data was performed to ensure a relatively normal distribution was maintained.

The histograms used to manually check the data were constructed using *E-Views*. The histograms representing the data series after the initial trimming and 'winsorising' procedures were completed are shown in Appendix F. Following this process; an *E-Views* program (shown in Appendix G) was run in order to calculate the monthly payoffs. As a final check, this program included a command to trim all data points to within three standard deviations of the mean.

4.2.5. Firm-specific attribute data and adjustments

'Firm-specific attributes' refer to financial information about a specific firm, such as a financial ratio, a change in that financial ratio, an accounting line item, or a technical indicator. In this study they are also referred to as 'style characteristics' or 'style factors', and when placed in the context of the CAPM they are also termed 'anomalies' or 'anomalous factors'.

The firm-specific attribute data for the 1468 companies was collected from the *Datastream* database, subject to availability, for the period August 2000 to August 2013, using a static monthly request repeated 156 times. While the empirical tests are only performed using the period August 2003 to August 2013, the data predating this period was used in the construction of some of the financial ratios and growth factors.

Datastream derives its firm-specific attributes data from the quoted published financial statements of listed companies, using consolidated reports when available and parent financials when necessary. There are many different 'datatypes' covering the same accounting and financial figures and ratios within the *Datastream* database, so the ones with the greatest number of observations were used. Some attributes were taken directly from *Datastream*, while others were constructed using *Datastream* information. The returns data collected for Section 4.2.4 was used to construct the momentum characteristics, and in the case of stocks that were excluded in accordance with adjustments required in the Sections above, the data was discarded.

A number of style characteristics were tested, including: the size effect, the value effect, the momentum effect, the growth effect, the risk effect, the leverage effect, and the emerging market effect. The firm-specific style characteristics are listed in Table 4.3, and grouped by their respective style group, code, characteristic and formula. Some of these characteristics have previously been tested and have been found to have a significant relationship with stock returns in specific countries, indices or sectors, but this is not a constraint or requirement.

Table 4.3: Firm-Specific Style Attributes

The table below lists the firm-specific style characteristics, grouped by style, which are tested in this analysis. Each style factor has a unique code, which is used throughout the report. The table also lists the *Datastream* 'datatype' that forms the basis for the firm-specific factor under investigation, as well as the formula that was used to calculate each factor. A *Datastream* definition for each of the 'datatypes' is given in Appendix H. These attributes will be tested against forward returns to determine whether style anomalies exist on a global scale.

Style Group	Factor	Code	Datatype	Formula
Value	Book Value to Share Price	PTB	PTBV	1 / PTBV
	Cash Flow to Share Price	CFP	PC	1 / PC
	Dividend Yield as a Percentage	DY	DY	DY
	Earnings Yield	EY	PE	1 / PE
	Sales to Share Price	SP	1505 P	1505 / P
	EBITDA to Share Price	EBP	DWED; NOSH; P	(DWED / NOSH) / P
Growth	% change in Sales - 6 months	S6	DWSL	[DWSL(t)-DWSL(t-6)] / DWSL(t)
	% change in Sales - 12 months	S12	DWSL	[DWSL(t)-DWSL(t-12)] / DWSL(t)
	% change in Sales - 24 months	S24	DWSL	[DWSL(t)-DWSL(t-24)] / DWSL(t)
	% change in Earnings - 6 months	E6	IDTDDEPS	[IDTDDEPS(t)-IDTDDEPS(t-6)] / IDTDDEPS(t)
	% change in Earnings - 12 months	E12	IDTDDEPS	[IDTDDEPS(t)-IDTDDEPS(t-12)] / IDTDDEPS(t)
	% change in Earnings - 24 months	E24	IDTDDEPS	[IDTDDEPS(t)-IDTDDEPS(t-24)] / IDTDDEPS(t)
	% change in Dividends - 6 months	D6	190	[190(t)-190(t-6)] / 190(t)
	% change in Dividends - 12 months	D12	190	[190(t)-190(t-12)] / 190(t)
	% change in Dividends - 24 months	D24	190	[190(t)-190(t-24)] / 190(t)
	12-month change in Dividends, to Price	DP12	190; P	[D(t)-D(t-12)] / P(t)
	6-month change in Earnings, to Price	EP6	IDTDDEPS; P	[IDTDDEPS(t)-IDTDDEPS(t-6)] / P(t)
	12-month change in Earnings, to Price	EP12	IDTDDEPS; P	[IDTDDEPS(t)-IDTDDEPS(t-12)] / P(t)
	24-month change in Earnings, to Price	EP24	IDTDDEPS; P	[IDTDDEPS(t)-IDTDDEPS(t-24)] / P(t)
	Payout Ratio	PR	POUT	POUT
	Return on Equity	ROE	DWRE	DWRE
	Return on Assets	ROA	DWRE; DWTA; 1301	DWRE*(DWTA-1301) / DWTA

	Asset Turnover	**STA**	**1505; NOSH; DWTA**	**(1505*NOSH) / DWTA**
	Dividend Cover	**DC**	**DCV**	**DCV**
	Operating Margin	**OM**	**713**	**713**
	CAPEX to Sales	**CXS**	**DWCX; 1505; NOSH**	**DWCX / (1505*NOSH)**
Momentum	1-month Prior Return	**MOM1**	**RI**	**[RI(t)-RI(t-1)] / RI(t-1)**
	3-month Prior Return	**MOM3**	**RI**	**[RI(t)-RI(t-3)] / RI(t-3)**
	6-month Prior Return	**MOM6**	**RI**	**[RI(t)-RI(t-6)] / RI(t-6)**
	12-month Prior Return	**MOM12**	**RI**	**[RI(t)-RI(t-12)] / RI(t-12)**
	24-month Prior Return	**MOM24**	**RI**	**[RI(t)-RI(t-24)] / RI(t-24)**
Size & Liquidity	Log of Price	**LnP**	**PI**	**LN [PI]**
	Log of MV	**LnMV**	**MV**	**LN [MV]**
	Log of Enterprise Value	**LnEV**	**1504**	**LN [1504]**
	% change in Turnover by Volume - 6 months	**TVO6**	**VO**	**[VO(t)-VO(t-6)] / VO(t-6)**
	% change in Turnover by Volume - 12 months	**TVO12**	**VO**	**[VO(t)-VO(t-12)] / VO(t-12)**
	% change in Turnover by Volume - 24 months	**TVO24**	**VO**	**[VO(t)-VO(t-24)] / VO(t-24)**
Risk	Standard Deviation	**STD**	**RI**	**StdDev[RI(t); RI(t-1); …; RI(t-12)]**
	Volatility	**VOL**	**RI**	**(StdDev)^2**
	Beta	**BET**	***BETA***	***BETA***
Leverage	Interest cover before tax	**ITBT**	**ICBT**	**ICBT**
	Debt to Equity	**DE**	**DWTA; 1301**	**1301 / (DWTA - 1301)**
	Debt to Assets	**DA**	**DWTA; 1301**	**1301 / DWTA**
Market	Emerging Market vs. Developed Market	**EM**	**GGISO**	**GGISO**

The following adjustments to the firm-specific attribute data were considered:

4.2.5.1. Growth Variables

Price and Momentum attributes are based on variables that change frequently and can be easily observed in the market, so it is possible to calculate one-month, three-month, six-month, one-year and two-year changes. Growth in dividend, earnings, and volume attributes are based on variables that are reported less frequently through interim financial statements, so it is necessary to be prudent in the analysis and therefore only six- month, one-year and two-year changes are calculated.

The cash earnings and earnings figures required for calculating growth attributes can take on negative or zero values, which could be problematic for percentage change figures, or cause a division by zero and consequent discontinuities in the data. In order to rectify this, an additional factor is derived where the denominator is replaced with the current price index P_t to give:

$$[(A_t - A_{t-x}) / P_t]$$

For consistency, an added growth in dividends factor was calculated in the same way.

4.2.5.2. Normal Distribution

Although the Ordinary Least Squares (OLS) regression employed in the following Chapters does not require the explanatory variables to be normally distributed, the natural log transform further reduces the effects of outliers and influential observations due to errors or abnormal events. The natural log will therefore be applied to the market value, enterprise value and price data to ensure that the data is normally distributed when testing the size effect.

4.2.5.3. Completeness

Any missing observations in the attribute data can be dealt with in a number of ways. While Haugen and Baker (1996) suggest assigning the mean attribute value to months where attribute data is missing, this approach may introduce statistical biases and therefore months with missing attribute data are simply omitted in this study.

4.2.5.4. Outliers

A similar process to that used on the returns data was performed for the firm-specific attribute dataset. The dataset was initially checked for extreme outliers, which were manually removed. The same 'winsorisation' method was then conducted, except that here the monthly mean and standard deviation across the shares was calculated using the firm-specific attribute data and performed for each attribute. A manual check was then conducted to ensure a relatively normal distribution for each attribute individually. The histograms of the trimmed firm-specific factors are shown in Appendix F. From these histograms it is clear that all the factors resemble a form of normal distribution, and can be used in the latter testing without adjustments.

4.2.5.5. Standardisation

A vital step with the firm-specific attribute data is the standardisation. The firm-specific attribute data is standardized to a zero mean and a standard deviation equal to one, in order to facilitate direct comparison with the regression coefficients. The standardisation makes it possible to compare the magnitudes of the slopes estimated in the cross-sectional regressions that follow in the next section. These trimmed and standardised factors are the basis of testing in later Chapters.

4.2.5.6. Dummy Variable

A dummy variable is used in the model in cases where the variable under review takes the form of qualitative as opposed to quantitative data and allows one to test factors such as 'Emerging' or Developed' against the market factor. The ISO geographical classification for each share is used in order to ascertain whether a stock is from an emerging or developed market. The IMF's "*Classifications of Countries Based on Their Level of Development*" (Nielsen; 2011) is then used to classify each geographical area into either an 'Emerging' or 'Developed' category. A '1' is assigned to an Emerging market stock, and a '0' is assigned to a Developed market stock. There are 27 Emerging and 26 Developed markets represented in this study.

4.2.6. Possible Bias and Solutions

The success of empirical studies can easily be flawed by several sources of bias. An objective of this study is therefore to minimize the effects of different forms of bias discussed below in an effort to ensure that the results and conclusions drawn are robust and reliable.

4.2.6.1. Data snooping

Haugen and Baker (1996) explain that the bias associated with data snooping occurs when researchers (a) examine the properties of a database or the results of other studies of a database, (b) build predictive models employing promising factors based in the previous results, and then (c) test the power of their models on the same database. They mention that the problem can be addressed by employing data from markets that have not been studied extensively, or predicting by using time periods that are new to analysis.

To remove the threat of data snooping to some extent, this study is conducted on a very large global sample that has not been the subject of much prior testing. The time-period is also very current and has not been tested in the same way before. The behaviour of the payoffs are also analysed to determine whether in-sample and out-sample tests are required.

4.2.6.2. Look Ahead Bias

Haugen and Baker (2006) describe the look-ahead bias as occurring when data items are used as predictive factors, but the values were unknown when the predictions would have been made. They give an example of the earnings-to-price ratio being used as a predictive factor, but the ratio is calculated with an earnings number that was not actually reported at the date of the prediction, leading to an exaggerated effectiveness of the factor, despite it having little or no real-time worth due to a lack of true predictive information at the time of forecasting.

In order to mitigate the look-ahead bias, the *Datastream* database was used to gather the data as *Datastream* only updates information once it becomes public knowledge. Thus data items can be used as predictive factors because they were publically known when prediction would have been made.

4.2.6.3. Survivorship bias

If a database systematically excludes significant numbers of firms that have become individually inactive, Haugen and Baker (1996) suggest that the data can be said to suffer from survival bias. They explain that if one observes the performance of only those companies that remain listed, one will probably find that the survivors' performance exceeds that of the market. If the factors used in prediction are somehow related to the probability of going inactive, failure to include inactive firms in the database would result in misleading estimates of significance and predictive power.

As with most studies over such a time period, this study is exposed to a degree of survivorship bias as a result of the sampling method; the top 1500 shares based on market value as at August 2013. The survivorship bias is, however, partially mitigated by the choice of sample with the top 1500 global shares by market value being the most stable and least likely to suffer from non-survival.

4.3. Descriptive statistics

An analysis of the sample's descriptive statistics was conducted to gain an initial understanding of the overall data pool. These descriptive statistics were useful when making adjustments to the data before the testing methodology was applied in order to ensure that the most robust and accurate results could be obtained.

As Acres (2007) notes, the sheer size and diversity of global data limits the number of useful statistics and summary measures that may be employed. However, descriptive statistics were calculated for each of the firm specific attributes for the August 2003 to August 2013 period across all 1468 firms employed in this analysis. These statistics were computed after the winsorisation process described above, but before standardisation.

Means, medians, and standard deviations were calculated for the revenue as well as firm-specific attributes over the entire period. The maximum, minimum, and number of observations were also calculated for each attribute over the whole testing period. While the distribution of the data is not an influencing consideration in the tests of the following Chapter, the medians and means were tested for skewness. All factors are found to be positively skewed, except for the natural logs of market value, enterprise value and share price.

Table 4.4: Descriptive Statistics

The table below lists the firm-specific style factors and returns data that is used for testing. The style factors are listed in order of their style grouping for comparative purposes. These descriptive statistics were calculated after the trimming and winsorisation procedure, but before standardisation of the factors. The overall number of observations for each style factor is shown, and emphasizes the statistical significance of such a large sample of shares. The mean, median, minimum and maximum is shown for each factor, as well as the standard deviation and skewness.

Style Factor	Observa-tions	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness
PTB	155064	0,538751	0,456621	4,000000	-2,000000	0,386786	2,076283
CFP	154259	0,132755	0,105932	1,000000	-1,000000	0,117853	1,690925
DY	160367	2,241158	1,870000	10,000000	0,000000	1,915385	1,014491
EY	148992	0,068532	0,059172	0,500000	0,000025	0,046051	2,862647
SP	153652	0,882137	0,598624	5,000000	0,000000	0,884964	1,917985
EBP	154426	0,206233	0,146291	1,999858	-0,995776	0,231445	3,147567
S6	152668	0,085889	0,031962	2,000000	-1,000000	0,239898	2,754842
S12	149865	0,191493	0,109154	2,996354	-1,000000	0,405203	2,790616
S24	144284	0,436225	0,227666	4,998702	-1,990848	0,750818	2,602525
E6	148680	0,031365	0,000000	2,000000	-1,000000	0,174260	5,754301
E12	145851	0,061496	0,000000	2,000000	-1,000000	0,244195	3,858878
E24	142979	0,192052	0,002137	5,000000	-1,000000	0,592904	4,228592
D6	131183	0,073783	0,015596	2,000000	-1,000000	0,291402	1,704139
D12	127343	0,151080	0,107143	2,000000	-1,000000	0,403453	0,790642
D24	128506	0,035112	0,003291	2,000000	-1,000000	0,184204	4,729625
DP12	124127	0,383176	0,240385	5,000000	-1,000000	0,758459	2,039583
EP6	148214	1665,7880	0,000000	10000,0000	-99670,2200	11164,9700	3,344601
EP12	140155	2426,1850	0,000000	10000,0000	-99389,9800	13890,6600	2,478714
EP24	128844	3396,3210	0,000000	10000,0000	-99770,0800	17241,1700	1,601800
PR	159665	32,691200	29,790000	100,000000	0,000000	25,387590	0,580805
ROE	162015	16,103210	14,690000	100,000000	-50,000000	14,126780	0,949278
ROA	144666	12,610580	11,107790	60,000000	-9,999155	9,501044	1,256256
STA	127492	0,758056	0,288961	4,999998	0,000000	1,055640	1,945638
DC	151839	2,829016	2,400000	12,000000	0,000000	2,004372	1,452218
OM	164385	17,248060	14,750000	96,720000	-39,920000	13,738930	1,094021
CXS	139418	0,292375	0,052805	4,998416	-1,894884	0,652908	3,918683
MOM1	161768	0,015692	0,014031	1,000000	-1,000000	0,100183	0,269644
MOM3	160796	0,047113	0,042523	1,000000	-1,000000	0,176240	0,245360
MOM6	159964	0,105154	0,088154	2,000000	-1,000000	0,281125	0,929165
MOM12	156894	0,200215	0,166568	2,000000	-1,000000	0,402688	0,772208
MOM24	153837	0,428173	0,287282	5,000000	-1,000000	0,744711	1,883698
LnP	158044	2,821250	3,141995	11,976660	-7,824046	1,561658	-0,429781
LnMV	157770	9,325943	9,303554	13,444010	0,076961	1,158016	-0,737897
LnEV	151243	16,500110	16,449190	20,866860	10,085680	1,272487	-0,020323

TVO6	139782	0,201104	-0,025472	4,000000	-1,000000	0,864632	1,612280
TVO12	142035	0,249578	0,003742	5,000000	-1,000000	0,921037	1,939536
TVO24	136791	0,357713	0,023936	6,000000	-1,000000	1,118192	2,007228
STD	88931	22,167230	10,214070	99,998710	0,000000	26,643940	1,272146
VOL	88931	1201,2780	104,3273	9999,7410	0,000000	2190,7990	2,196722
BET	169279	1,024500	1,004000	2,311000	0,024000	0,423783	0,307522
ITBT	160119	9,319473	3,700000	119,970000	-39,920000	16,620180	3,253205
DE	159493	0,347336	0,259239	1,994806	0,000000	0,336707	1,713653
DA	165509	0,227986	0,208760	0,998713	0,000000	0,166571	0,760778
EM	177628	0,248638	0,000000	1,000000	0,000000	0,432224	1,163114
RET	162061	0,015256	0,013505	1,000000	-1,000000	0,100016	0,278122

4.4. Summary and Conclusion

This Chapter introduced the company share returns and firm-specific attribute datasets. The returns, financial, and accounting information for the top 1500 global shares, based on market value, were gathered from *Datastream* for the period August 2000 to August 2013. Preference shares and shares without adequate returns data were removed from the sample and a trading filter applied. Both the returns and attributes data were winsorised, and all necessary adjustments were made. A smoothing process left 1468 liquid, globally represented shares, ready for testing in the following Chapters.

Data-snooping bias was addressed by using a very large global sample that has not been the subject of many tests before, and a current time-period that not been tested in the same way before. The use of *Datastream* as a tool for data mining minimized any look-ahead bias which may have existed in the sample since information is only updated once it becomes public knowledge. The comparability between stocks and style factors is facilitated through the use of a common currency, the U.S. Dollar, and the process of standardisation. Survivorship bias remains a concern due to the nature of the sampling; however, the degree of this bias should be minimal due to the underlying nature of the companies sampled.

The following Chapter details the procedure to be followed in order to test the existence of style anomalies on a global scale, investigate the behaviour of style anomalies, and construct a style characteristic based model of the cross-section of global returns.

- 5 -

Methodology

"When human judgment and big data intersect there are some funny things that happen."

- Nate Silver (2012)

5.1. Introduction

This Chapter examines the methodology required to test the existence of style anomalies, and investigate the empirical relationships between monthly stock returns and firm-specific style attributes in the global markets. As discussed in previous Chapters, there are numerous firm-specific factors that have been able to explain the variation in share returns empirically. However, there is very little evidence available to support whether these style factors exist on a global scale, or if they can be used in global asset-pricing and return-prediction strategies.

Empirical literature suggests that a correctly specified asset-pricing model should explain all expected variations in asset returns. Therefore, the unexpected portion of asset returns, also known as pricing errors, should not be able to be predicted using style characteristics. However, due to the presence of irrationality in the market and the limitations of existing asset-pricing models, it is postulated that these style characteristics have the ability to explain asset prices to some extent. The methodology for investigating the existence and behaviour of these style anomalies will be discussed in this Chapter, and a model for global asset pricing will be investigated.

Section 5.2 discusses the methodology for investigating the existence of style anomalies, using both unadjusted and risk-adjusted returns, and then looks at adjustments that may need to be made to avoid bias results. Section 5.3 thereafter discusses the methodology used to analyse the behaviour of the univariate factors identified in Section 5.2. Section 5.4 explains the methodology used to construct a multi-factor model for pricing global assets, and Section 5.5 provides a summary of testing methodology and concludes.

5.2. The Existence of Style Anomalies: Univariate Analysis

There are essentially two methods for testing the existence of style anomalies: creating style-mimicking portfolios and running cross-sectional regressions. Robertson and van Rensburg (2003) find that "asset pricing models are better specified using attribute values rather than factor loadings", however they conclude that "attributes and loadings both represent 'exposures', while returns on factor-mimicking portfolios and cross- sectional regression slopes both represent 'rewards' and either approach may be used to model the covariance structure of returns". Therefore, as there seems to be no empirical difference between creating factor-mimicking portfolios and running cross-sectional regressions, this study will use the cross-sectional regression slope approach.

In line with van Rensburg and Robertson (2003), Janari (2005) and Acres (2007), a Fama-MacBeth (1973) method will be used to test the existence and significance of the style effects. This test allows for negative style ratios and the joint analysis of many variables. All inclusions of individual stocks into the Fama-MacBeth tests are subject to the restrictions and adjustments described in Chapter 4. In addition to a Fama-MacBeth method, a 'Full Data' method will be employed to check the accuracy of the Fama-MacBeth results, and assist in the derivation of a multi-factor asset pricing model. After the data points are prepared, the procedure outlined below will be followed in order to determine the existence and significance of style factors in global stock returns.

5.2.1. Fama-MacBeth Method

Empirical research suggests that the Fama-MacBeth (1973) methodology provides a robust method of testing the theoretical models used to describe returns. The aim of the Fama-MacBeth univariate cross-sectional (monthly) analysis is to uncover the identity of the global style factors that are able to explain stock variation.

Each of the factors listed in Table 4.3 are tested individually using a one-factor cross-sectional regression similar to the Fama-MacBeth (1973). As described in 4.2.5.5, the firm-specific factors are first standardised in order to allow for direct comparison between the different factors' regression coefficients.

The trimmed, smoothed and standardised firm-specific factors for the 1468 global shares are thus the foundation for testing, as follows:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{i,t} + \varepsilon_{i,t+1} \tag{5.1}$$

Where:

- $r_{i,t+1}$ is the observed return on share *i* at the end of the month *t+1* (the dependent variable)
- $\Upsilon_{0,t+1}$ is the cross-sectional slope intercept at time *t+1*, estimated using ordinary least squares
- $\Upsilon_{1,t+1}$ is the cross-sectional slope coefficient at time *t+1*, estimated using ordinary least squares
- $A_{i,t}$ is the standardised value of the attribute of share *i* under consideration at the end of the month t
- $\varepsilon_{i,t+1}$ is the monthly error term, the unexplained residual return on firm i at time t+1

The methodology starts with the postulate that style factors can explain portfolio returns. It is possible to determine the premium or payoff that is rewarded for each stock's exposure to each firm-specific style factor by regressing the forward monthly returns on each stock against its factor exposures in each period. The resulting regression coefficients reflect the magnitude of the cross-sectional relationships between monthly forward stock returns and firm-specific attributes. These monthly cross-sectional coefficients are then averaged to get an overall slope or payoff to each factor. Observations on asset returns have been gathered over the 121-month period, and we would like to test whether style factors can contribute to the explanation the variation in these asset returns, and ascertain the payoff awarded for the exposure to each factor.

The regressions are carried out using the Ordinary Least Square (OLS) regression method, over the 121-month period, for the 1468 shares, using a panel data setup in *E-Views*. There are many assumptions required when using an OLS regression specific to the error term, which are noted in Section 5.2.6 below.

5.2.2. 'Full Data' Method

The 'Full Data' regression method is a univariate analysis, conducted over the entire period, with the aim of revealing the identity of the global style factors that are best able to explain stock variation before and after adjustment for systematic risk. This method is used as a test of the results of the Fama-MacBeth method (described above), as a method of risk-adjustment, and as an additional tool for understanding the behaviour of style anomalies.

Each of the factors listed in Table 4.3 are tested individually using a one-factor OLS regression, using a panel data setup in *E-Views*. As with the Fama-MacBeth regression, the trimmed, smoothed and standardised factors for the 1468 global shares are the foundation for testing. The 'Full Data' regression is outlined as follows:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{i,t} + \varepsilon_{i,t+1} \tag{5.2}$$

Where:

- $r_{i,t+1}$ is the observed forward return on share *i* (the dependent variable)
- $\Upsilon_{0,t+1}$ is the slope intercept over the full period, estimated using ordinary least squares
- $\Upsilon_{1,t+1}$ is the slope coefficient over the full period, estimated using ordinary least squares
- $A_{i,t}$ is the standardised value of the attribute of share *i* under consideration
- $\varepsilon_{i,t+1}$ is the error term, the unexplained residual return on firm *i* at time *t+1*

Each stock's returns at the end of the month are regressed against the firm-specific style factors during each month, to determine each stock's exposure to these factors. As with the Fama-MacBeth method, it is then possible to determine the premium that is rewarded to investors for each unit of exposure to each factor. The biggest difference between the Fama-MacBeth and 'Full Data' methods is that the Fama-MacBeth regression is run monthly and then the cross-section of slopes is averaged, whereas the 'Full Data' regression is run over the entire period in one go. The resulting regression coefficients reflect the magnitude and direction of the relationship between forward stock returns and firm-specific attributes over the whole 121-month period.

The 'Full Data' regressions are carried out using the OLS regression method, over the 121-month period, for the 1468 shares, using a panel data setup in *E-Views*. Statistically, the full-data method is more accurate as there are more observations and it comprises more robust calculations rather than using averages. Therefore, while both methods have merit and are tested, the results of the full-data method are the primary method of factor selection for inclusion in the multi-factor index model constructed in later chapters.

5.2.3. Unadjusted Returns

In line with the methodology used by van Rensburg and Robertson (2003), each of the characteristics listed in Table 4.1 is tested on an individual basis using a one-factor cross-sectional regression, as described above in the Fama and MacBeth discussion.

It is important to note that the stock returns in each month are regressed on the attribute values at the beginning of the same month in order to ensure that the regression tests are of a predictive rather than descriptive nature. The regression tests are conducted in *E-Views* using a program to standardise all factors, check that all data is crimped to within 3 standard deviations, run the monthly regressions, and collect the monthly slopes. The code for this program is shown in Appendix G.

Using the Fama-MacBeth method, the resulting time-series of regression coefficients represents the reward or payoff to each characteristic in each month. The time series averages are calculated for each factor and are subjected to Student's (1908) t-test (hereafter referred to as the 't-test'). The t-test is used to identify the firm-specific style attributes whose predictive capability and payoff is significantly different from zero. The t-test is defined as follows:

$$t = \frac{(\bar{\gamma}_1 - 0)}{\sigma_{\gamma_1}/\sqrt{N}} \tag{5.3}$$

Where:

- $\bar{\gamma}_1$ is the time series average of the cross-sectional regression coefficient for the attribute under consideration (as calculated in equation 5.1.)
- $\sigma_{\gamma 1}$ is the time series standard deviation of the cross-sectional regression coefficients for the attribute under consideration
- N is the number of observations in the time series

It must also be noted that the standard deviations used in the t-test can be constructed in this way as the stock returns are roughly independently and identically distributed (shown in Appendix F).

Fama MacBeth (1973) notes that: "as long as one is not concerned with precise estimates of probability levels, interpreting t-statistics in the usual way does not lead to serious errors". Therefore significant style factors are identified as having a time-series mean cross-sectional slope coefficient significantly different from zero using a t-test. As a minimum level of significance, a t-statistic of 2 in a two-tailed t-test will is used as the threshold. This implies a p-value of 0,05 and a 95% probability that the factor is significantly different from zero. In this way the t-statistic is used to identify attributes with significant forecasting potential, however it does not test the accuracy of the forecasts made.

A 'Full Data' regression is also conducted on the unadjusted returns, as explained in Section 5.2.2, and compared to the Fama-MacBeth time series of payoffs method. The 'Full Data' regressions are run on the firm-specific style factors and unadjusted forward return observations from the entire period. The t-statistics are automatically calculated as the slope divided by the standard error, and included with the univariate regression output. The full comparison between the two methods is discussed in Section 5.3.

Therefore, based on the results of the regressions and t-tests above, factors are identified which have significant explanatory and forecasting power, and which could potentially be included into a multi-factor model for pricing assets and predicting returns.

5.2.4. Risk-Adjusted Returns

In order to determine whether the style factors identified in the unadjusted analysis can explain share returns beyond what is already explained by the market risk factor; *Beta*, a risk adjustment is conducted on the dataset of share returns.

There are many ways to perform the risk adjustment. The CAPM-centered risk-adjustment method first allows the market to explain returns and only thereafter allows the attributes to explain returns, which is conservative and therefore reduces bias. The CAPM risk-adjusted returns are calculated as follows:

$$\left(\alpha_i + \varepsilon_{i,t}\right) = \left(r_{i,t} - r_{f,t}\right) - \beta_i\left(r_{m,t} - r_{f,t}\right) \tag{5.4}$$

Where:

- α_i is the intercept term
- $\varepsilon_{i,t}$ is the monthly error term, the unexplained residual return on firm *i* at time *t+1*
- β_t is the sensitivity to market risk, estimated using ordinary least squares regression
- $\left(\alpha_i + \varepsilon_{i,t}\right)$ is the total return for share *i* in month *t* that is not explained by the market *Beta*
- $r_{m,t}$ is the return on the world market for month *t*
- $r_{i,t}$ is the return on share *i* for month *t*
- r_f is the risk-free rate of return in month *t*

The error term for each share, calculated monthly, is recorded and added to the estimated intercept term. Together these terms result in a set of monthly CAPM risk-adjusted returns for all shares in the sample. By substituting the $r_{i,t+1}$ from equation 5.1 for (α_i + $\varepsilon_{i,t+1}$), the univariate cross-sectional regression of the CAPM risk-adjusted share returns on firm-specific style attribute values at the beginning of the period can be restated as:

$$\left(\alpha_i + \varepsilon_{i,t+1}\right) = \gamma_{0,t+1} + \gamma_{1,t+1}A_t + \varepsilon_{i,t+1} \tag{5.5}$$

As discussed in the previous section, the time series averages of the cross-sectional regression coefficients are calculated in this way, and subjected to the t-test in order to identify significant attributes.

Another method of risk-adjustment would be to use an arbitrage pricing model, which would test whether the factors have explanatory power beyond the risk factors in the APT model. As there is no single accepted APT model for global stocks, this method would require significant cluster analysis and assumptions. Acres (2007) finds that world market indices cluster into two groups, which can be broadly defined as the 'developed markets indices' and the 'emerging markets indices' so one could use these two factors in the APT model, but more testing would need to be conducted before this method is used.

Empirical evidence from van Ransburg and Robertson (2003), Janari (2003) and Acres (2007) suggest that risk-adjusting the returns does not yield significantly different results. The effect of risk-adjusting the stock return dataset with the CAPM or the two-factor APT model does not materially affect the cross-sectional explanatory power of the attributes. Empirical observations by Page (1996) further note that any misspecification found in a model constructed within the CAPM framework, is not improved by instead using an APT approach. The APT is therefore no better than the CAPM as a method of risk adjustment.

For this study, the method of choice for risk-adjustment is to run a two-factor regression for each of the firm-specific style factors along with the *Datastream*-calculated *Beta* for each stock in order to determine whether the style factors can explain share returns beyond what is already explained by the market risk *Beta*, as follows:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1}A_t + \gamma_{2,t+1}\beta_t + \varepsilon_{i,t+1} \qquad (5.6)$$

Where:

- $r_{i,t+1}$ is the realised return on share *i* for the month *t+1* (the dependent variable)
- $\Upsilon_{0,t-1}$ is the cross-sectional slope intercept at time *t+1*, estimated using ordinary least squares regression
- A_t is the standardised value of the attribute of the share under consideration at the end of each month *t*

- $\Upsilon_{1,t+1}$ is the cross-sectional slope coefficient of A at time *t+1*, estimated using ordinary least squares
- β_t is the share's sensitivity to the market as calculated by *Datastream* at the end of each month *t*
- $\Upsilon_{2,t+1}$ is the cross-sectional slope coefficient of *Beta* at time *t+1*, estimated using ordinary least squares
- $\varepsilon_{i,t+1}$ is the monthly error term, the unexplained residual return on share *i* at time *t+1*

This multi-factor regression is conducted over the full 10-year period, using data that was both trimmed and standardised. Unadjusted slopes and t-stats are compared directly to risk-adjusted slopes and t-stats to ascertain whether the presence of the market risk *Beta* has a material effect on the style-factor coefficient and t-stat measure of significance. The styles with the most significant '*Beta* effect' are noted and the difference in t-stat significance is analysed in depth.

5.2.5. Strength of Forecasting Ability

As the t-stat only measures the significance and not the accuracy of the forecasts made, the strength of each factor's forecasting ability is determined using Grinold's (1989) Information Coefficient (IC). The IC is calculated for each style factor using the time series of forward returns. The IC is generally defined as the Pearson (1896) correlation coefficient between attribute payoffs.

In a univariate setting, however, the IC is calculated as the Pearson (1896) correlation between the time series of attribute values under consideration, and the time series of forward returns linked to the attribute:

$$IC = \rho\left[A_{i,t}, r_{i,t+1}\right] \qquad (5.7)$$

Therefore:

$$IC = \rho_{A,r} = \frac{\sum_{t=1}^{n}\left(r_{i,t+1} - \bar{r}_x\right)\left(A_{i,t} - \bar{A}_x\right)}{n-1} \qquad (5.8)$$

Where:

- $\rho_{A,r}$ is the correlation coefficient between the value of the firm-specific attribute and the forward returns
- $r_{i,t+1}$ is the realised return for share *i* at the end of month *t+1*
- $\bar{r}_i$ is the mean realised return over the testing period for firm-specific attribute *i*
- $A_{i,t}$ is the value of the firm-specific attribute for share *i* at the end of month *t*
- $\bar{A}_i$ is the mean firm-specific attribute for share *i*
- n is the number of monthly observations in the time series

Banz (2004) notes that an IC of 0.1 is considered 'high' and therefore a firm-specific style factor with an IC of 0.1 or greater has significant predictive power.

A further calculation that can be done to test the accuracy of the forecasting ability is the Information Ratio (IR), which is based on the IC calculated above. The IR calculates the variation across the monthly IC's and thereby provides a measure of statistical significance. There are many versions of the IR, but in this study the Qian and Hua (2004) version will be used:

$$IR = \frac{\overline{IC}}{\sigma(IC)} \tag{5.9}$$

Where:

- $\overline{IC}$ is the mean monthly IC
- σ(IC) is the standard deviation of the monthly IC

The IC and IR tests will be used in addition to the t-statistics to measure the significance of the style anomalies and the accuracy and strength of each style factor's forecasting ability.

5.2.6. Adjustments for Bias

As with any study there are many areas where bias can creep in which can taint the results and in some cases render them useless. As a result, it is important to acknowledge where the possibility for bias lies and mitigate the risk as best as possible:

- Firstly, there are many assumptions required when using an OLS regression specific to the error term. The stochastic error term, ε, represents the variation of those variables not explicitly explained by the model, but could also represent a measurement error. Tests on this error term need to be conducted to ensure that the errors are statistically independent of each other, the expected value of the errors is always zero, and the errors are normally distributed.

- Fama-MacBeth regression outputs produce standard errors, which have been corrected for cross-sectional correlation, and not for time-series autocorrelation. This is usually not a problem when analysing stocks, as stock returns tend to have weak time-series autocorrelation in daily and weekly holding periods, but exhibit strong autocorrelation over long time-periods. This means Fama-MacBeth regressions may be inappropriate, and it may be necessary to correct these standard errors for time series and cross-sectional correlation in the error term.

- Another potential issue with the error term could arise if there is autocorrelation in the error term, and the autocorrelation is not random. This may be a sign that a variable or style factor is missing from the analysis. This omitted variable bias can potentially be avoided by conducting a factor analysis on the correlated error term, and then using that as a factor so that the new error term is completely random.

5.3. Behaviour of Univariate Factors

The results from the univariate analysis give an indication of which style factors are significant within the global context. The next step, understanding the behaviour of these significant factors, is key to a better understanding of style anomalies within the global market, and a better understanding of the global market in general. It is also necessary to test the significant factors in the presence of risk and other factors in order to determine the strength of their forecasting ability within an asset-pricing model.

This Section describes the methodology necessary to analyse whether the risk-adjustment is necessary to include in the model, and which method of regression is best utilised to identify the most significant factors. A cumulative monthly payoff analysis is discussed and correlated factors are identified in order to construct the most accurate multi-factor model that can be used in global asset pricing and return prediction.

The calculations within this Section were conducted in *E-Views* for the period from August 2003 to August 2013. All 44 style factors were analysed, but most attention was paid to significant factors at a 5% level.

5.3.1. Fama-MacBeth vs. 'Full Data' Method

Once a significant factor is identified using the cross-sectional regressions, the average monthly slopes and accompanying t-stats from the Fama-MacBeth method are compared to the 'Full Data' method results, where the slopes and t-statistics were calculated for the entire period and using all observations. This is done primarily as a form of validation for both methods of results, and to identify any anomalies within the sets of results.

Statistically speaking, the 'Full Data' regression t-statistics are more accurate as they contain more observations, have more degrees of freedom, and involve more robust calculations than averages. Therefore while both methods have merit and are tested, the results of the Fama-MacBeth method are used primarily to analyse the existence of style anomalies, the cumulative monthly payoffs, and correlation between factors; while the 'Full Data' results are used to analyse the behaviour of style anomalies in a multi-factor setting, and is the primary source for choosing factors to be included in the multi-factor index model constructed in later Chapters.

5.3.2. Unadjusted vs. Risk-Adjusted Factors

In order to determine whether the style factors can explain share returns beyond what is already explained by the market risk *Beta*, a risk adjustment was conducted on the dataset of share returns. As described in Section 5.2.4, a two-factor 'Full Data' regression for each of the firm-specific style factors along with the *Datastream* calculated *Beta* for each stock was conducted in order to determine whether the style factors remain significant in the presence of the market risk factor. It must be noted that the *Beta* used in this analysis is calculated by *Datastream* as the sensitivity to each domestic market.

The results from the 'Full Data' single-factor regression of each firm-specific factor are compared to the results from the 'Full Data' two-factor regression with *Beta* included. This comparison of both slope coefficients and t-statistic values of significance assist in determining whether the risk-adjustment is necessary in the multi-factor model, and more importantly whether the style attributes exist within the market risk model or independent of it. The big question is if the presence of the *Beta* has a material effect on the style-factor coefficient and significance.

As mentioned previously, empirical evidence from van Rensburg and Robertson (2003), Janari (2003) and Acres (2007) suggest that risk-adjusting the returns does not yield significantly different results. It will be interesting to note whether this is confirmed on a global scale, and whether there is a significant relationship between risk measures and forward returns. The firm-specific style factors with the most significant '*Beta* effect' are noted and the difference in t-statistic significance is analysed in depth.

5.3.3. Cumulative Monthly Payoff Analysis

Once significant factors are identified and checked over the full period, their behaviour over the period is analysed in order to better understand the different styles, assess their predictive capabilities and determine whether further in-sample or out-sample testing needs to be conducted. In order to analyse the behaviour of the significant factors, cumulative slope graphs are produced for each factor of the form:

$$CP_{f,t} = CP_{f,t-1}(1 + S_{f,t-1}) \quad (5.10)$$

Where:

- $CP_{f,t}$ is the cumulative monthly payoff to factor *f* at time *t*
- $CP_{f,t-1}$ is the cumulative payoff to the particular factor *f* as at time *t-1*
- $S_{f,t-1}$ is the monthly payoff slope to the particular factor *f* as at time *t-1*
- $CP_0 = 1$

The payoffs are analysed for each factor individually, as well as within each style grouping. As the monthly slopes indicate the sensitivity to each factor, the cumulative slopes therefore indicate the cumulative sensitivities over time. These cumulative monthly payoffs, calculated for each of the firm-specific attributes, illustrate their relative capacities to generate returns, and their behaviour during various global economic conditions. One of the most interesting periods for analysis will be the recent 2008-2009 global recessionary period brought about by the U.S. credit crisis.

5.3.4. Identifying Correlated Attributes

Following the cumulative slope analysis, the relationship between the significant factors is tested using Pearson's (1896) correlation. The Pearson correlation (hereafter referred to as the 'correlation') coefficient is used as the measure of similarity in clustering of the average payoff slopes calculated for each firm-specific style attribute using the Fama-MacBeth (1973) methodology, and is defined as:

$$\rho_{x,y} = \frac{\sum_{t=1}^{n}(\gamma_{x,t} - \bar{\gamma}_x)(\gamma_{y,t} - \bar{\gamma}_y)}{n-1} \quad (5.11)$$

Where:

- $\rho_{x,y}$ is the correlation coefficient between the slopes of the style factors x and y
- $\Upsilon_{x/y,t}$ is monthly slope derived from style factor x/y for month t
- $\Upsilon_{x/y}$ is the mean monthly slope for the time-series of slopes derived from style factor x/y
- n is the number of monthly slope observations in the time series

In this way, the correlation coefficients are calculated for every pair of factors throughout the period using the unadjusted time series of payoffs to the respective factor. The correlation coefficient is the most appropriate measure of similarity and is used to cluster the monthly payoffs to each factor into homogenous style groups. If the correlation is less than perfect it is likely that more than one factor is necessary to account for the total style effect.

A correlation matrix is prepared, which displays the correlation coefficient between each factor, on a scale of -1 to 1, where -1 and 1 are perfectly correlated and 0 is perfectly uncorrelated. In this analysis, a pair of attributes with a correlation coefficient greater than 0.7 or less than -0.7 is considered to have a high degree of correlation. The correlation assists in finding the most accurate classification of each firm-specific factor into the specific style groups, and helps to ensure that the factors used in the stepwise regression model all have unique explanatory power.

5.4. Modeling Style Anomalies – Multivariate Analysis

Based on the results of the existence, significance and behavioural analysis above, this Section identifies factors that could potentially be included in a multi-factor model for asset pricing and return prediction. The proposed factors for multi-factor model testing are identified from the univariate results as the firm-specific factors where the payoff slope coefficient is significantly different from zero using a t-test. In this way, the multivariate relationship between firm-specific style attributes and unadjusted forward returns is investigated.

The need for a multivariate analysis is emphasised by Michaud (1999), who explains that the performance of individual style attributes needs to be investigated in the presence of others style attributes. In isolation, a firm-specific style factor may explain a significant portion of the variation in returns, but relationships and dynamics between factors can result in one factor being subsumed by another. The aim of this Section, therefore, is to analyse the slope payoffs to the individual firm-specific style factors, and related t-statistics, in a multifactor setting, in order to arrive at a model that can potentially forecast global returns.

Multivariate OLS regressions are conducted over the period from August 2003 to August 2013, taking the form:

$$r_{i,t+1} = \gamma_{0,t+1} + \sum_{f=1}^{m} \gamma_{f,t+1} A_{f,t} + \varepsilon_{i,t+1} \tag{5.12}$$

Where:

- $r_{i,t+1}$ is the observed return on stock *i* at time *t+1*
- $A_{f,t}$ is the value of firm-specific factor *f* under consideration at time *t*
- $\Upsilon_{0,t+1}$ is the OLS regression intercept term at time *t+1*
- $\Upsilon_{f,t+1}$ is the OLS regression coefficient of firm-specific factor *f* at time *t+1*
- $\varepsilon_{i,t+1}$ is the unexplained residual return on stock *i* at time *t+1*

Only unadjusted stock returns are considered in this section due to the similarity of results from the unadjusted and risk-adjusted analysis (shown later in Section 6.3.2). The procedure outlined below is followed in order to construct a characteristic-based model of the cross-section of worldwide returns.

5.4.1. Stepwise Regression

There are numerous methods of testing factors and forming multi-factor models, including principal components, maximum-likelihood and various least-squares methods. In order to represent the relationship between sets of interrelated style factors and global share returns, a multi-factor model is constructed using a manual stepwise regression method and a forward selection approach. In accordance with the multivariate analysis of Acres (2007), this stepwise regression builds on the factors that were identified in the univariate analysis as significantly explaining variation in stock returns.

A stepwise regression method for building a model involves the successive addition or removal of variables based on the t-statistics of their estimated coefficients. There are many approaches one can take within the stepwise regression methodology: forward, where one begins with no variables in the model and proceeds forward, adding one variable at a time; backward, where one begins with all possible variables in the model and proceeds backwards, removing one variable at a time; and bidirectional, where one uses a combination of the forward and backward by testing at each step whether variables need to be included or excluded. Because all methods yield very similar, if not identical results, it was decided that the forward method would be used for this analysis.

At each step, for each factor currently in the model, the t-statistic for its estimated slope coefficient is calculated. These t-statistics are then compared to the t-statistics of the coefficient that each variable would have if the next variable were added. If the t-statistics with the added variable are still significant, the variable is generally added. The process continues until there is little to no explanatory benefit to adding any more factors. As Van Rensburg and Slaney (1997) note, one should also consider the exchange between the economy offered by a simple model with fewer factors, and the increased accuracy and explanatory power that is enjoyed with more factors, when deciding how many factors to include. A manual check is also conducted to assess whether each addition makes economic and logical sense.

It is important to measure the total variance captured by the factor and thus its explanatory power. While studying the sequence of variables added, the adjusted R-squared value is a vital measure, as, unlike the standard R-squared value, it will only increase if the added variable carries with it untapped explanatory power beyond what could be attributed to 'random noise'. If a factor's explanatory power is held in a factor or combination of factors already in the model, the addition of the extra factor will actually cause the adjusted R-squared to decrease, denoting the factor as surplus to the requirements of the model. The variables present in the model when the adjusted R-squared reaches its maximum are retained for the final predictive model.

5.4.2. Adjustments for Bias

- A stepwise regression model, by its nature, is constantly exploring a large number of potential models. As such, a primary concern is the choice of the most appropriate selection criteria. The drawback of choosing inappropriate selection criteria is that it can be subject to over-fitting data in a sense that the value of the stepwise regression results is very specific to the sample that was used to derive it, and may not have as much value outside of the sample. The stepwise method tends to capitalize on sampling error and thus tends to yield results that are not replicable. This problem can be mitigated if the criteria for adding or removing variables are strict enough.

- With the use of a stepwise regression, there is no guarantee that the most accurate model, or in fact any level of accurate model that can be constructed from the available factors, will be found by this step-by-step searching technique. It is therefore important to study the sequence of factors added or deleted once the process terminates in order to ascertain whether the addition or removal makes economic and not only statistical sense. A manual check is necessary to assess whether the addition or removal of any more variables might lead to an improvement of the model.

5.4.3. Multi-factor Model Testing

While this is not the focus of this study, there is a great deal of testing required on the constructed multi-factor model for pricing global assets before it can be used. The tests would specifically need to assess the forecasting ability of the model by comparing expected and actual returns. These tests, as explained below, are areas for further research.

One method of testing for errors in any model created by step-wise regression is to test the model against a set of data that was not used to create it. This can be done by constructing the model based on a subset of the dataset available, and using the 'hold-out' subset to verify the model. This form of testing could also be done with completely new data. Measures of accuracy could include the actual standard error, or mean error between the forecasted value and the actual value in the hold-out sample. This is particularly useful when testing whether the model has the capacity to be generalised.

As discussed in the univariate analysis, Acres (2007) suggests the use of the Grinold (1989) 'Information Coefficient' (IC) as a measure of accuracy, but this time calculated using the time series of expected and actual returns. The expected returns would be calculated using the multi-factor model as a predictor. The IC can therefore be defined as the Pearson (1896) correlation between the expected monthly stock return and the observed, realised monthly sector return as follows:

$$IC = \rho\left[E\left(r_{i,t+1}\right), r_{i,t+1}\right] \qquad (5.13)$$

Where:

- $E(r_{i,t+1})$ is the expected return for share *i* at the end of month *t+1*, calculated using the multi-factor forecasting model
- $r_{i,t+1}$ is the realised return for share *i* at the end of month *t+1*

Another test on the accuracy of the forecasts is the 'Information Ratio' (IR), which differs from the IC in that it also takes into account the variation across the monthly IC's and in doing so it provides a measure of statistical significance. As discussed in the univariate analysis, there are many versions of the IR but once again the Qian and Hua (2004) version will be used:

$$IR = \frac{\overline{IC}}{\sigma(IC)} \tag{5.14}$$

Where:

- $\overline{IC}$ is the mean monthly IC
- $\sigma(IC)$ is the standard deviation of the monthly IC

5.5. Summary and Conclusion

Using a combination of the Fama-MacBeth regression method, and the 'Full Data' regression method, the overall payoff to investing in each of the 44 different firm-specific style attributes was calculated. The significance of the payoff was calculated through the use of t-tests, and the forecasting accuracy analysed through 'Information Coefficient' and 'Information Ratio' calculations. These tests ultimately determine whether style anomalies exist on a global scale.

A comparison between the Fama-MacBeth and 'Full Data' methods serves both to validate the univariate results and determine which method's results should be used for which purpose. A comparison between the unadjusted and *Beta*-adjusted payoff and t-statistic results then helps to determine whether the significance of style anomalies is affected by the presence of a market risk factor, and whether it is the risk factor or the style anomaly which explains the greatest amount of variation. A cumulative monthly payoff analysis is used to describe the behaviour of each firm-specific style factor and style grouping over the period, and an analysis of the correlation between each factor assists in the validation of style groupings and the overall understanding of the interrelationships between different style attributes.

Using the existence, significance, and behaviour results, a forward stepwise regression technique is used to examine the significance of the style attributes within a multivariate setting, and construct a multi-factor model for use in global return forecasting and global asset pricing. Adjusted R-squared measures and t-statistics examined closely when constructing the model.

Areas for further research and testing include alternate methods for calculating the significance and accuracy of the firm-specific style factor payoffs, the behaviour of different styles during different economic climates, and out-of-sample testing of the multi-factor model.

-6-

Empirical Results

"Providence has its appointed hour for everything. We cannot command results, we can only strive."

- Mahatma Gandhi (1939)

6.1. Introduction

This Chapter examines the results found when analysing the existence of style anomalies and empirical relationships between monthly stock returns and firm-specific style attributes in the global market. In accordance with the methodology presented in Chapter 5, this Chapter determines whether firm-specific factors are able to explain the variation in share returns empirically, and more specifically which factors are best able to do so.

While empirical studies have found that style characteristics have the ability to explain asset prices to some extent in individual countries and on a smaller scale of testing, the results in this Chapter have a global portfolio focus and mark the beginning of a universal global market understanding and global asset-pricing model. The behaviour of, and relationships between the style anomalies are investigated and a model for global asset pricing is constructed.

All results are obtained using the smoothed, trimmed and standardised firm-specific factors and forward returns of the top 1468 global firms obtained from *Datastream*, over the period from August 2003 to August 2013, and analysed using *E-Views* statistical software.

Section 6.2 discusses the univariate results regarding the existence of style anomalies, using both unadjusted and risk-adjusted returns, and using both the Fama-MacBeth and 'Full Data' methods for testing. Section 6.3 then discusses the behaviour of the univariate factors identified in Section 6.2, through an analysis of risk-adjustment, regression methods, cumulative monthly slope payoffs, and correlation between factors. Section 6.4 discusses the results of the multi-factor analysis and constructs a multi-factor model for pricing global assets. Section 6.5 then summarises the empirical results of this analysis and concludes.

6.2. Univariate Results

After the data points were prepared, the procedure outlined in Section 5.2 was followed in order to determine the existence and significance of style anomalies in global stock returns. The results using both unadjusted and risk-adjusted returns, and using both the Fama-MacBeth and 'Full Data' regression methods for testing, are discussed below. The accuracy and strength of each factor's forecasting ability is discussed thereafter.

6.2.1. Fama-MacBeth Unadjusted Returns

The univariate cross-sectional ordinary least squares (OLS) regression results were obtained by regressing the unadjusted returns on the various sector-specific attributes every month. The Fama-MacBeth regression was conducted every month for the 121 months under review, and for each of the 44 firm-specific factors against the forward returns of each of the 1468 global stocks. The t-statistic, mean monthly regression coefficient, standard error, and style grouping are shown in Table 6.1. The results are sorted in descending order according to the absolute values of the t-statistics. Nine attributes were found to be significant at a 5% significance level.

Table 6.1: Fama-MacBeth Regression of Unadjusted Returns

The table below lists the univariate cross-sectional ordinary least squares regression results, which were obtained when regressing the unadjusted returns on the various sector-specific attributes for the 1468 global shares every month for the full 10-year period. The t-statistic, mean monthly regression coefficient, standard error, and style grouping for each factor are shown. The results are sorted in descending order according to the absolute values of the t-statistics, and it is clear that first nine bolded factors are significant at the 5% level.

Factor	Average Slope	Standard Error	Student's t-stat	Style
STA	**-0,002581**	**0,004041**	**-7,026378**	**Growth**
CXS	**0,003041**	**0,005298**	**6,313982**	**Growth**
EBP	**0,003717**	**0,009021**	**4,531760**	**Value**
DC	**0,001616**	**0,005623**	**3,161029**	**Growth**
EM	**0,003134**	**0,012434**	**2,772959**	**Emerging Market**
D24	**0,002250**	**0,009793**	**2,527512**	**Growth**

TVO24	**0,001556**	**0,007185**	**2,381897**	**Size / Liquidity**
TVO6	**0,001503**	**0,007444**	**2,221034**	**Size / Liquidity**
PR	**-0,001534**	**0,007858**	**-2,147427**	**Growth**
TVO12	0,001246	0,007102	1,929262	Size / Liquidity
E12	0,001091	0,006366	1,884420	Growth
EY	0,002053	0,011989	1,883558	Value
LNEV	-0,000472	0,002863	-1,814236	Size / Liquidity
E6	0,001127	0,007671	1,615565	Growth
LNMV	-0,000419	0,002881	-1,600167	Size / Liquidity
ROA	0,000824	0,006241	1,452840	Growth
S6	0,001000	0,007574	1,451943	Growth
E24	0,000769	0,006327	1,337597	Growth
EP24	0,000623	0,005534	1,238409	Growth
S24	0,000799	0,007739	1,135840	Growth
EP12	0,000650	0,006492	1,101308	Growth
MOM24	0,001666	0,017623	1,039878	Momentum
SP	0,000831	0,009619	0,950252	Value
S12	0,000726	0,008430	0,947515	Growth
EP6	0,000464	0,006183	0,826321	Growth
D6	0,000707	0,009945	0,781858	Growth
DY	-0,000490	0,007280	-0,741012	Value
ROE	0,000492	0,007848	0,689826	Growth
MOM12	0,001113	0,018763	0,652593	Momentum
MOM3	0,000843	0,015132	0,612588	Momentum
MOM1	-0,000631	0,013149	-0,528267	Momentum
DE	-0,000106	0,002371	-0,489971	Leverage
MOM6	0,000763	0,017933	0,467982	Momentum
ITBT	0,000280	0,007685	0,401170	Leverage
VOL	-0,000241	0,007090	-0,373576	Risk
CFP	-0,000089	0,002906	-0,336779	Value
BET	0,000601	0,020053	0,329882	Risk
OM	-0,000188	0,007827	-0,263676	Growth
PTB	0,000054	0,002506	0,238723	Value
LNP	-0,000040	0,002413	-0,180516	Size / Liquidity
DA	0,000059	0,005412	0,120401	Leverage
D12	-0,000053	0,008789	-0,066382	Growth
STD	0,000033	0,008074	0,044837	Risk
DP12	0,000026	0,009455	0,030263	Growth

Sales/Total Assets has the most significant t-statistic. This could indicate that the global market places high importance on a firm's efficiency. The slope is negative, however, which indicates that increasing Total Assets, relative to Sales, leads to increasing returns. This is the opposite of a growth effect, and indicates the significance of total assets when evaluating the cross-section of global returns.

CAPEX/Sales is the next most significant t-stat. This growth factor indicates that a relatively large portion of return variation can be explained by the growth style. It seems a high CAPEX, which shows future growth and return potential for a stock, is linked to high forward returns. This is connected directly to the significant yet negative Sales/Total Assets characteristic payoff, as increasing CAPEX generally increases Total Assets in the long run, so relative to the Sales figure it appears that CAPEX and Total Assets are rewarded in a similar way.

EBITDA/Price displays the third highest significance, and is a very strong value factor. A high EBITDA (Earnings before Interest, Tax, Depreciation, Amortisation) relative to the share price is evidence of a firm's return potential that is underpriced by the market, and carries a significant payoff from a return perspective.

The high significance of the Emerging Market factor indicates that there is a positive payoff to investing in emerging market stocks within a global market context. This is economically accurate, as emerging market stocks would have access to high growth potential, and carry an added level of risk for which the investor would require compensation in the form of higher returns.

The 24-month Growth in Dividends shows a significant positive payoff, and makes sense as Dividends are directly linked to total returns - calculated as a combination of capital appreciation of the share and the Dividends Received. A growth in Dividends is therefore empirically linked to higher total returns over a 2-year period. Growing Dividends can indicate confidence both in the firm's results and the firm's ability to maintain a higher or growing Dividend, and is therefore economically linked to increased returns.

The Payout Ratio has a significantly negative payoff. An increasing Dividend per share, as a percentage of Earnings per share, indicates that the Growth in Dividends is not necessarily sustainable, as Earnings should increase to be able to cover the increase in Dividends. The 'Dividend Cover' factor is the direct inverse of the 'Payout Ratio' factor, as it represents the number of times the Earnings can cover the Dividend. The 'Dividend Cover' factor has a significantly positive payoff. This acts as a confirmation of the negative Payout Ratio, and shows that high Earnings relative to Dividends are positively rewarded by returns. These significant payoffs are evidence of the growth style effect.

The 6-month % change in Turnover by Volume, and the 24-month % change in Turnover by Volume, both have significantly positive payoffs. This indicates that the volatility risk associated with high turnover by volume of shares is rewarded with high returns.

It is noteworthy that the factors within the Risk style group, namely the Standard Deviation, Volatility, and *Beta* factors, are all found to be insignificant using the Fama-MacBeth method. This indicates a direct contrast to the widely accepted risk-return framework presented initially by Markowitz (1952). The Markowitz theory postulates a significant positive relationship between stock returns and the relevant risk measure. The findings of this study, however, contend that both *Beta* and Standard Deviation are found to have a positive payoff for risk, while Volatility exhibits a negative payoff.

From this Fama-MacBeth univariate analysis, it is interesting that no momentum style factors, and few size and value variables, were found to have significant payoffs. This will be analysed further when the Fama-MacBeth results are compared to the 'Full Data' results in Section 6.3.1, and when the behaviour of the monthly univariate results is analysed through cumulative slopes in Section 6.3.3.

6.2.2. 'Full Data' Method Unadjusted Returns

The univariate cross-sectional ordinary least squares (OLS) regression results were obtained when regressing the unadjusted returns on the various firm-specific attributes over the complete period. The full-period regression was conducted for each of the 44 firm-specific factors against the forward returns of each of the 1468 global stocks. The t-statistic, regression coefficient, standard error, and style grouping are shown in Table 6.2. Twenty-five attributes were found to be significant at a 5% significance level.

Table 6.2: 'Full Data' Regression of Unadjusted Returns

The table below lists the univariate cross-sectional ordinary least squares regression results, which were obtained when regressing the unadjusted returns on the various firm-specific attributes for the 1468 global shares over the full 10-year period. The t-statistic, mean monthly regression coefficient, standard error, and style grouping for each factor are shown. The results are sorted in descending order according to the absolute values of the t-statistics, and it is clear that the first twenty-five factors are significant at the 5% level.

Factor	Slope	Standard Error	t-stat	Style
EBP	**0,003762**	**0,000313**	**12,01632**	**Value**
EM	**0,002563**	**0,000254**	**10,07539**	**Emerging Market**
CXS	**0,002995**	**0,000344**	**8,697826**	**Growth**
STA	**-0,002536**	**0,000294**	**-8,638352**	**Growth**
EY	**0,001889**	**0,000290**	**6,520607**	**Value**
PR	**-0,001492**	**0,000257**	**-5,811374**	**Growth**
DC	**0,001568**	**0,000271**	**5,786496**	**Growth**
MOM24	**0,001546**	**0,000275**	**5,613766**	**Momentum**
D24	**0,001968**	**0,000391**	**5,036266**	**Growth**
TVO24	**0,001413**	**0,000287**	**4,917646**	**Size / Liquidity**
TVO6	**0,001226**	**0,000282**	**4,347449**	**Size / Liquidity**
TVO12	**0,001200**	**0,000284**	**4,229479**	**Size / Liquidity**
S6	**0,001148**	**0,000320**	**3,584146**	**Growth**
MOM12	**0,000874**	**0,000260**	**3,362605**	**Momentum**
SP	**0,000838**	**0,000267**	**3,136522**	**Value**
E6	**0,001335**	**0,000426**	**3,134748**	**Growth**
ROA	**0,000850**	**0,000278**	**3,058168**	**Growth**
E12	**0,001003**	**0,000338**	**2,964259**	**Growth**
MOM1	**-0,000743**	**0,000266**	**-2,794372**	**Momentum**
E24	**0,000955**	**0,000343**	**2,780920**	**Growth**
MOM3	**0,000723**	**0,000261**	**2,769465**	**Momentum**
S24	**0,000768**	**0,000295**	**2,606035**	**Growth**
S12	**0,000761**	**0,000303**	**2,515847**	**Growth**
D6	**0,000705**	**0,000325**	**2,170985**	**Growth**
DY	**-0,000520**	**0,000251**	**-2,071235**	**Value**
ROE	0,000549	0,000280	1,959955	Growth
BET	0,000467	0,000250	1,864405	Risk
EP24	0,000535	0,000332	1,609358	Growth
LNEV	-0,000408	0,000272	-1,502681	Size / Liquidity
ITBT	0,000439	0,000311	1,412397	Leverage
EP12	0,000463	0,000360	1,283992	Growth
LNMV	-0,000342	0,000277	-1,235085	Size / Liquidity
MOM6	0,000224	0,000266	0,839988	Momentum
PTB	-0,000231	0,000286	-0,807364	Value
OM	-0,000197	0,000264	-0,748398	Growth
D12	-0,000186	0,000282	-0,657098	Growth
CFP	-0,000179	0,000314	-0,569354	Value

EP6	0,000224	0,000408	0,549466	Growth
VOL	-0,000173	0,000364	-0,476085	Risk
DE	0,000097	0,000279	-0,348867	Leverage
DP12	0,000090	0,000303	-0,296100	Growth
STD	0,000091	0,000344	0,263989	Risk
LNP	0,000002	0,000271	0,005847	Size / Liquidity
DA	0,000001	0,000258	-0,004639	Leverage

EBITDA/Price displays the highest significance, and is a very strong value factor. A high EBITDA (Earnings Before Interest, Tax, Depreciation, Amortisation) relative to the share Price is evidence of firm value that is underpriced by the market, and carries a significant positive payoff from a return perspective. While the value effect is well documented empirically, this particular firm-specific factor has not often been the subject of testing. The factor that has empirically shown significance as a value factor is the Earnings/Price factor, or Earnings Yield, which is also shown to have a significant positive payoff, although not as significant as the EBITDA/Price measure. The EBITDA/Price measure certainly warrants further testing in future. One further value factor that has a significant payoff is the Sales/Price ratio.

The factor with the second highest level of significance is the 'Emerging Market' factor, which indicates that there is a positive payoff to investing in emerging market stocks within a global market context. As explained previously, this is economically accurate, as emerging market stocks would include access to high growth potential, and an added level of risk for which the investor would require compensation in the form of higher returns. This factor has not been tested extensively before, but seems to have very significant explanatory and predictive power and should therefore be the subject of further testing.

As with the Fama-MacBeth results, the Sales/Total Assets factor and the CAPEX/Sales factor are both significant. Increasing Total Assets, relative to Sales, leads to increasing returns; and a high CAPEX, which shows growth and future potential for a stock, is linked to high forward returns. A large Asset base and high growth potential seem to lead to high forward returns.

Unlike with the Fama-MacBeth results, the Momentum effect, specifically the 24-month, 12-month, and 3-month momentum, has significant positive payoffs within a global context when analysed using the 'Full Data' results. This speaks specifically to a medium-to-long term momentum effect where well performing stocks continue to outperform, and poor performing stocks continue to underperform. The 1-month momentum also has a significant payoff, however it is a negative payoff. This indicates the short-term reversals that occur in the market due to over-reaction and investor irrationality. There is therefore an implied validity to the short-term contrarian investment strategy in a global market, which in itself can be seen as a style strategy.

The 24-month Growth in Dividends shows a significant positive payoff, and, as with the Fama-MacBeth univariate results, this makes sense as dividends are directly linked to total returns and a growth in dividends is therefore linked to higher returns over a 2-year period. The 6-month Growth in Dividends is also significant using the 'Full Data' method.

As with the Fama-MacBeth results, the Payout Ratio has a significantly negative payoff, and the Dividend Cover factor has a significantly positive payoff. Other growth effects become significant with the 'Full Data' method, including the 6-month, 12-month, and 24-month growth in Sales, and 6-month, 12-month, and 24-month growth in Earnings, as well as the Return on Assets ratio.

The 6-month % change in Turnover by Volume, 12-month % change in Turnover by Volume, and the 24-month % change in Turnover by Volume all have significantly positive payoffs. In line with the Fama-MacBeth results, this indicates that the volatility risk associated with high turnover volume of shares is rewarded with high returns.

Yet again it is interesting to note that the factors within the Risk style group, namely the Standard Deviation, Volatility, and *Beta* factors, are all found to be insignificant using the 'Full Data' method. As with the Fama-MacBeth discussion, this indicates a direct contrast to the risk-return framework presented by Markowitz (1952), which assumes a significant positive relationship between stock returns and the risk measure. Both *Beta* and Standard Deviation are also found to have positive payoffs, while Volatility exhibits a negative payoff. This is an initial indication that the style factors should remain significant when combined with a risk factor in a multivariate setting.

6.2.3. 'Full Data' Method Risk-adjusted Returns

The univariate cross-sectional ordinary least squares regression results were obtained by regressing the stock returns on both the firm-specific attributes for each share, and the *Beta* of each share, over the full period. The 121-month two-factor regression was conducted for each of the firm-specific factors and the individual stock *Beta*s against the returns for each of the 1468 global stocks. The firm-specific factor coefficient, *Beta* coefficient, firm-specific factor t-statistic, and *Beta* t-statistic are shown in Table 6.3. These results will be compared to the unadjusted 'Full Data' results in Section 6.3. The results are sorted in the same order as the unadjusted 'Full Data' method results, in order to facilitate direct comparison. Twenty-seven firm-specific factors, and fourteen corresponding *Beta*s were found to be significant at a 5% significance level.

It must be noted that the *Beta* used in this analysis is calculated by *Datastream* as the sensitivity of each stock to its domestic market.

Table 6.3: 'Full Data' Regression of *Beta*-adjusted Returns

The table below lists the univariate cross-sectional ordinary least squares regression results, which were obtained by regressing the stock returns on both the firm-specific attributes for each share, and the *Beta* of each share, for the 1468 global shares over the full 10-year period. The firm-specific factor coefficient, *Beta* coefficient, firm-specific factor t-statistic, and *Beta* t-statistic are shown. The results are sorted in the same order as the unadjusted 'Full Data' method results, in order to facilitate direct comparison, and it is clear that twenty-seven firm-specific factors, and fourteen corresponding *Beta*s are significant in the cross-sectional two-factor regression tests at a 5% significance level.

Factor	Risk Adjusted Factor Coefficient	*Beta* Coefficient	Risk Adjusted Factor t-stat	*Beta* t-stat
EBP	0,003523	0,000538	**11,20113**	0,898181
EM	0,00282	0,001714	**10,83619**	**2,890662**
CXS	0,003146	0,001297	**9,036937**	**2,065491**
STA	-0,002592	0,002063	**-8,781925**	**3,083023**
EY	0,001924	-0,001278	**6,573273**	**-2,122598**
PR	-0,001502	0,000692	**-5,642512**	1,101348
DC	0,001484	0,001104	**5,426515**	1,758469
MOM24	0,001574	0,001393	**5,65396**	**2,347426**
D24	0,001953	0,001039	**4,978275**	1,668547
TVO24	0,001368	0,001474	**4,708864**	**2,370746**

TVO6	0,001194	0,00098	**4,183297**	1,570584
TVO12	0,001339	0,001339	**4,664749**	**2,175708**
S6	0,001161	0,001006	**3,593097**	1,673199
MOM12	0,000755	0,000966	**2,867818**	1,637253
SP	0,00081	-0,000187	**2,986396**	-0,314463
E6	0,001465	0,00143	**3,403755**	**2,346948**
ROA	0,000855	0,000399	**3,02165**	0,6332998
E12	0,001044	0,001654	**3,059357**	**2,705409**
MOM1	-0,00062	0,00113	**-2,308527**	1,915029
E24	0,000973	0,00179	**2,8045**	**2,928639**
MOM3	0,00078	0,000916	**2,954586**	1,551791
S24	0,000826	0,001192	**2,779851**	1,970769
S12	0,00074	0,001186	**2,422938**	1,965212
D6	0,000682	0,000671	**2,086522**	1,072696
DY	-0,000528	0,001004	**-2,056265**	1,68736
ROE	0,000567	0,000834	1,982909	1,380601
EP24	0,00075	0,001017	**2,229104**	1,614335
LNEV	-0,000285	0,001274	-1,042079	1,995023
ITBT	0,000373	0,001128	1,191572	1,861105
EP12	0,00077	0,000987	**2,115126**	1,599386
LNMV	-0,000229	0,001256	-0,820206	**2,006984**
MOM6	0,000118	0,000948	0,436336	1,608218
PTB	-0,000234	0,00124	-0,813541	1,963642
OM	-0,000173	0,000856	-0,639878	1,431466
D12	-0,000303	0,001181	-1,064288	1,872253
CFP	-0,000195	0,001248	-0,618264	1,97274
EP6	0,000462	0,000958	1,125351	1,572687
VOL	-0,000386	0,002103	-1,059297	**2,526312**
DE	-0,0000301	0,001435	-0,107129	**2,300274**
DP12	-0,000142	0,000815	-0,464491	1,283202
STD	-0,000145	0,002065	-0,417226	**2,47563**
LNP	0,0000308	0,001194	0,112979	1,908389
DA	0,00000111	0,001181	-1,064288	1,872253

Table 6.3 shows that there are many significant *Beta* coefficients with significant payoffs when combined with the various firm-specific factors in a multivariate analysis, but the significant firm-specific factor payoffs from the previous univariate results seem to retain their significance for the most part. A thorough comparison is conducted in Section 6.3.2.

6.2.4. Strength of Forecasting Ability

To determine the strength of each factor's forecasting ability, Grinold's (1989) Information Coefficient (IC) was calculated for each style factor using the time series of returns. In this univariate setting the IC is defined as the Pearson (1896) correlation coefficient between each of the firm-specific attributes and the forward returns. The IC and IR are calculated in accordance with Section 5.2.5. Banz (2004) notes that an IC of 0.1 is considered “high” and therefore a model with an IC of 0.1 of larger is considered to have predictive power. A further test for the accuracy of the forecasts is the Information Ratio (IR), which also takes into account the variation across the monthly ICs and thereby provides a measure of statistical significance. The IC and IR for each of the firm-specific factors are displayed in Table 6.4 below.

Table 6.4: IC and IR Results for Forecasting Accuracy

The table below compares the strength of each firm-specific factor’s forecasting ability obtained when using the Information Coefficient and Information Ratio calculations, based on the correlation between returns and attribute values for the 44 factors and 1468 shares over the 121-months. The firm-specific factor, t-stat, IC, and IR are shown. The results are sorted in descending order of accuracy (IC).

Factor	Information Coefficient (IC)	Information Ratio (IR)
MOM12	0,035957794	0,164703465
MOM24	0,031877959	0,168672546
EBP	0,030802635	0,218118953
EY	0,023220475	0,149343032
ROA	0,019724967	0,156727755
TVO6	0,01863238	0,16022771
EM	0,01827716	0,102433518
S24	0,017942495	0,14495097
DY	0,016229896	0,115657773
CXS	0,015144234	0,153517485
D24	0,014773334	0,12264179
ROE	0,014450214	0,112746843
D12	0,014400769	0,116275911
DC	0,011835437	0,094536912
S12	0,011775384	0,099596156
MOM3	0,011060926	0,060672824

D6	0,01066164	0,089346756
E6	0,010320022	0,122845158
S6	0,010263646	0,087659902
TVO12	0,00953391	0,092003368
ITBT	0,009121636	0,090040191
STD	0,008208559	0,058833445
E12	0,007990248	0,087196283
TVO24	0,00744719	0,06221909
EP24	0,007362299	0,07409309
SP	0,006494328	0,052200439
MOM6	0,005666124	0,02644819
EP6	0,005409745	0,05704615
VOL	0,004037623	0,034456426
E24	0,003696156	0,041109821
OM	0,000324566	0,002905598
BET	0,000191832	0,000982211
EP12	-0,001894204	-0,019043415
DA	-0,002401593	-0,021274035
DP12	-0,004142279	-0,034027867
LNP	-0,004984139	-0,057703235
PR	-0,007415276	-0,057780874
PTB	-0,008185736	-0,088128919
CFP	-0,009579985	-0,105539173
DE	-0,018042041	-0,19536625
LNEV	-0,018811247	-0,227648094
LNMV	-0,019277507	-0,240502613
MOM1	-0,025113179	-0,150325129
STA	-0,037391336	-0,378713582

From Table 4.6 above it appears that while the various factors have significant payoffs individually, they may not have very strong forecasting ability in a univariate setting. None of the IC measures are above 0,1 and therefore none of the factors can be deemed to have strong predictive power in isolation. The IR measures show that none of the factors are deemed statistically significant forecasters of returns in the absence of other factors. In this way, the IR measures validate the IC results. This could indicate that the style factors should be used in shaping investment decisions rather than in forecasting returns at a univariate level.

6.3. Relationship between Factors

The results from the univariate analysis shown in Section 6.2 above can be used to construct a multi-factor model in an effort to explain global returns. Before this can be done, however, it is necessary to analyse whether the risk-adjustment is necessary to include in the model, and which method of regression is optimal to identify the most significant factors. It is also beneficial to analyse the cumulative monthly payoffs and identify correlated factors in order to form a better understanding of the behaviour of the style factors, and ultimately to construct the most accurate multi-factor model.

After the data points were prepared, the procedure outlined in Section 5.3 was followed in order to determine the behaviour of significant style factors in global stock returns. The direction of the payoff is vital to understanding the factor behaviour.

6.3.1. Fama-MacBeth vs. 'Full Data' Method

Once significant factors were identified in Section 6.2, the average monthly slopes and t-stats from the Fama-Macbeth method were compared to the 'Full Data' method where the slopes and t-stats were calculated for the entire period and using all observations. This was done primarily as a form of validation for the Fama-MacBeth results, but also to determine which results should be used as a base for the multi-factor testing.

Table 6.5: Comparison of Fama-MacBeth and 'Full Data' Results

The table below compares the univariate cross-sectional ordinary least squares regression results obtained when using the Fama-MacBeth method and the 'Full Data' method using the same data and over the same period. The firm-specific factor coefficient, Standard Deviation and t-statistic for each method are shown. The results are sorted in the same order as the unadjusted Fama-MacBeth method results, in order to facilitate direct comparison.

Method:	F-M	Full	F-M	Full	F-M	Full
Factor	**Average Slope**	**Slope**	**Standard Deviation**	**Standard Error**	**Calculated t-stat**	**t-stat**
STA	-0,002581	-0,002536	0,004041	0,000294	-7,026378	-8,638352
CXS	0,003041	0,002995	0,005298	0,000344	6,313982	8,697826
EBP	0,003717	0,003762	0,009021	0,000313	4,531760	12,01632

DC	0,001616	0,001568	0,005623	0,000271	3,161029	5,786496
EM	0,003134	0,002563	0,012434	0,000254	2,772959	10,07539
D24	0,002250	0,001968	0,009793	0,000391	2,527512	5,036266
TVO24	0,001556	0,001413	0,007185	0,000287	2,381897	4,917646
TVO6	0,001503	0,001226	0,007444	0,000282	2,221034	4,347449
PR	-0,001534	-0,001492	0,007858	0,000257	-2,147427	-5,811374
TVO12	0,001246	0,001200	0,007102	0,000284	1,929262	4,229479
E12	0,001091	0,001003	0,006366	0,000338	1,884420	2,964259
EY	0,002053	0,001889	0,011989	0,000290	1,883558	6,520607
LNEV	-0,000472	-0,000408	0,002863	0,000272	-1,814236	-1,502681
E6	0,001127	0,001335	0,007671	0,000426	1,615565	3,134748
LNMV	-0,000419	-0,000342	0,002881	0,000277	-1,600167	-1,235085
ROA	0,000824	0,000850	0,006241	0,000278	1,452840	3,058168
S6	0,001000	0,001148	0,007574	0,000320	1,451943	3,584146
E24	0,000769	0,000955	0,006327	0,000343	1,337597	2,780920
EP24	0,000623	0,000535	0,005534	0,000332	1,238409	1,609358
S24	0,000799	0,000768	0,007739	0,000295	1,135840	2,606035
EP12	0,000650	0,000463	0,006492	0,000360	1,101308	1,283992
MOM24	0,001666	0,001546	0,017623	0,000275	1,039878	5,613766
SP	0,000831	0,000838	0,009619	0,000267	0,950252	3,136522
S12	0,000726	0,000761	0,008430	0,000303	0,947515	2,515847
EP6	0,000464	0,000224	0,006183	0,000408	0,826321	0,549466
D6	0,000707	0,000705	0,009945	0,000325	0,781858	2,170985
DY	-0,000490	-0,000520	0,007280	0,000251	-0,741012	-2,071235
ROE	0,000492	0,000549	0,007848	0,000280	0,689826	1,959955
MOM12	0,001113	0,000874	0,018763	0,000260	0,652593	3,362605
MOM3	0,000843	0,000723	0,015132	0,000261	0,612588	2,769465
MOM1	-0,000631	-0,000743	0,013149	0,000266	-0,528267	-2,794372
DE	-0,000106	0,000097	0,002371	0,000279	-0,489971	-0,348867
MOM6	0,000763	0,000224	0,017933	0,000266	0,467982	0,839988
ITBT	0,000280	0,000439	0,007685	0,000311	0,401170	1,412397
VOL	-0,000241	-0,000173	0,007090	0,000364	-0,373576	-0,476085
CFP	-0,000089	-0,000179	0,002906	0,000314	-0,336779	-0,569354
BET	0,000601	0,000467	0,020053	0,000250	0,329882	1,864405
OM	-0,000188	-0,000197	0,007827	0,000264	-0,263676	-0,748398
PTB	0,000054	-0,000231	0,002506	0,000286	0,238723	-0,807364
LNP	-0,000040	0,000002	0,002413	0,000271	-0,180516	0,005847
DA	0,000059	0,000001	0,005412	0,000258	0,120401	-0,004639
D12	-0,000053	-0,000186	0,008789	0,000282	-0,066382	-0,657098
STD	0,000033	0,000091	0,008074	0,000344	0,044837	0,263989
DP12	0,000026	0,000090	0,009455	0,000303	0,030263	-0,296100

The first important observation is that there are no factors that were found to be significant at a 5% level using the Fama-MacBeth method, that are not also found to be significant using the 'Full Data' method. This is an initial form of validation of the results in Section 6.2.

A further important observation is that the difference between the Fama-MacBeth average slopes and the 'Full Data' slopes is minimal. This is another degree of validation of the results, and indicates that either method can be used in multi-factor testing.

A key difference between the Fama-MacBeth results and the 'Full Data' results is the t-stat, which indicates the significance of the firm-specific style factor's payoff as being different from zero. At a 5% significance level, a t-stat in a two-tailed test in excess of 2 is considered significantly different from zero. A significant t-stat therefore implies the categorical existence of a style anomaly. The 'Full Data' results indicate that many more factors are significant, and most t-stats are much higher than their Fama-MacBeth counterparts. This is particularly noteworthy as the slopes themselves are very similar.

It appears that the standard error is the cause for the deviation in significance of the firm-specific style factors between the Fama-MacBeth and 'Full Data' methods. The Fama-MacBeth standard deviation for each of the firm-specific factors is significantly higher than those of the 'Full Data' method, indicating that the data points are more dispersed, thus increasing the margin of error.

The 'Full Data' method is statistically more accurate as it contains a greater number of observations, has more degrees of freedom, and involves more robust calculations. The Fama-MacBeth method, however, comprises monthly observations and is therefore better for time-series behavioural interpretation. Therefore, the Fama-MacBeth method is used primarily to analyse the existence of style anomalies, the cumulative monthly payoffs, and correlation between factors; while the 'Full Data' results are the primary source for choosing factors to be included in the multi-factor index model.

6.3.2. Unadjusted vs. *Beta*-adjusted Factors

Using the results from Sections 6.2.2 and 6.2.3 above, a comparison of both slope coefficients and t-statistic values of significance was conducted in order to determine whether the presence of the market risk *Beta* has a material effect on the style-factor coefficients and significance. This comparison will assist in determining whether the risk-adjustment is necessary in the multi-factor model, and more importantly whether the style attributes exist within the market risk model or independent of it. The firm-specific style factors with the most significant *Beta* effect are noted below, and the difference in t-stat significance is analysed in depth.

Table 6.6: Comparison of Unadjusted and *Beta*-Adjusted Results

The table below compares the univariate cross-sectional ordinary least squares regression results obtained using the 'Full Data' method, when regressing the firm-specific factor itself against returns, compared to regressing both the firm-specific factor and the *Beta* in a two-factor regression against returns, over the same 121-month period. The firm-specific factor coefficient for the single-factor regression is shown next to the firm-specific factor coefficient and *Beta* coefficient for the two-factor regression. The results are sorted in the same order as the unadjusted 'Full Data' method results, in order to facilitate direct comparison.

		Risk (*Beta*) Adjusted	
Factor	**'Full Data' Coefficient**	**Factor Coefficient**	***Beta* Coefficient**
EBP	**0,003762**	0,003523	0,000538
EM	**0,002563**	0,00282	0,001714
CXS	**0,002995**	0,003146	0,001297
STA	**-0,002536**	-0,002592	0,002063
EY	**0,001889**	0,001924	-0,001278
PR	**-0,001492**	-0,001502	0,000692
DC	**0,001568**	0,001484	0,001104
MOM24	**0,001546**	0,001574	0,001393
D24	**0,001968**	0,001953	0,001039
TVO24	**0,001413**	0,001368	0,001474
TVO6	**0,001226**	0,001194	0,00098
TVO12	**0,001200**	0,001339	0,001339
S6	**0,001148**	0,001161	0,001006
MOM12	**0,000874**	0,000755	0,000966
SP	**0,000838**	0,00081	-0,000187
E6	**0,001335**	0,001465	0,00143
ROA	**0,000850**	0,000855	0,000399
E12	**0,001003**	0,001044	0,001654
MOM1	**-0,000743**	-0,00062	0,00113
E24	**0,000955**	0,000973	0,00179
MOM3	**0,000723**	0,00078	0,000916
S24	**0,000768**	0,000826	0,001192
S12	**0,000761**	0,00074	0,001186
D6	**0,000705**	0,000682	0,000671
DY	**-0,000520**	-0,000528	0,001004
ROE	0,000549	0,000567	0,000834
EP24	0,000535	0,00075	0,001017
LNEV	-0,000408	-0,000285	0,001274

ITBT	0,000439	0,000373	0,001128
EP12	0,000463	0,00077	0,000987
LNMV	-0,000342	-0,000229	0,001256
MOM6	0,000224	0,000118	0,000948
PTB	-0,000231	-0,000234	0,00124
OM	-0,000197	-0,000173	0,000856
D12	-0,000186	-0,000303	0,001181
CFP	-0,000179	-0,000195	0,001248
EP6	0,000224	0,000462	0,000958
VOL	-0,000173	-0,000386	0,002103
DE	0,000097	-0,0000301	0,001435
DP12	0,000090	-0,000142	0,000815
STD	0,000091	-0,000145	0,002065
LNP	0,000002	0,0000308	0,001194
DA	0,000001	0,00000111	0,001181

A comparison of the slope coefficients of the firm-specific style factors before and after the risk-adjustment process yields the results in Table 6.6 above. Within the 25 significant factors at a 5% level, the absolute difference between unadjusted and risk-adjusted factor slopes is between 1% and 17%, with a mean of 0% and a median of -1%. This indicates that the market risk *Beta* does not have a material effect on the style-factor coefficients. The most significant difference (17%) is that of the one-month momentum factor, which could be a result of the very small coefficient on which even a small deviation is significant, but also indicates the high volatility experienced over shorter time-periods.

When analysing the *Beta* coefficient after the two-factor regression, it is clear that *Beta* is rewarded to some extent when regressed in addition to the firm-specific factor. However, the significance of this reward will be analysed in the t-statistic discussion below.

Therefore based on the coefficient analysis it seems that style anomalies exist independently of market risk. The firm-specific style factors with the most significant *Beta* effect, and the difference in the t-stats before and after risk adjustment, are analysed and reported in Table 6.7 below.

Table 6.7: Comparison of Unadjusted and *Beta*-Adjusted Results

The table below compares the univariate cross-sectional ordinary least squares regression results obtained using the 'Full Data' method, when regressing the firm-specific factor itself against returns, compared to regressing both the firm-specific factor and the *Beta* in a two-factor regression against returns, over the same 121-month period. The firm-specific factor t-stat for the single-factor regression is shown next to the firm-specific factor t-stat and *Beta* t-stat for the two-factor regression. The results are sorted in the same order as the unadjusted 'Full Data' method results, in order to facilitate direct comparison.

		Risk Adjusted	
Factor	**'Full Data' t-stat**	**Factor t-stat**	***Beta* t-stat**
EBP	**12,01632**	11,20113	0,898181
EM	**10,07539**	10,83619	2,890662
CXS	**8,697826**	9,036937	2,065491
STA	**-8,638352**	-8,781925	3,083023
EY	**6,520607**	6,573273	-2,122598
PR	**-5,811374**	-5,642512	1,101348
DC	**5,786496**	5,426515	1,758469
MOM24	**5,613766**	5,65396	2,347426
D24	**5,036266**	4,978275	1,668547
TVO24	**4,917646**	4,708864	2,370746
TVO6	**4,347449**	4,183297	1,570584
TVO12	**4,229479**	4,664749	2,175708
S6	**3,584146**	3,593097	1,673199
MOM12	**3,362605**	2,867818	1,637253
SP	**3,136522**	2,986396	-0,314463
E6	**3,134748**	3,403755	2,346948
ROA	**3,058168**	3,02165	0,6332998
E12	**2,964259**	3,059357	2,705409
MOM1	**-2,794372**	-2,308527	1,915029
E24	**2,780920**	2,8045	2,928639
MOM3	**2,769465**	2,954586	1,551791
S24	**2,606035**	2,779851	1,970769
S12	**2,515847**	2,422938	1,965212
D6	**2,170985**	2,086522	1,072696
DY	**-2,071235**	-2,056265	1,68736
ROE	1,959955	1,982909	1,380601
EP24	1,609358	2,229104	1,614335
LNEV	-1,502681	-1,042079	1,995023
ITBT	1,412397	1,191572	1,861105
EP12	1,283992	2,115126	1,599386
LNMV	-1,235085	-0,820206	2,006984
MOM6	0,839988	0,436336	1,608218
PTB	-0,807364	-0,813541	1,963642

OM	-0,748398	-0,639878	1,431466
D12	-0,657098	-1,064288	1,872253
CFP	-0,569354	-0,618264	1,97274
EP6	0,549466	1,125351	1,572687
VOL	-0,476085	-1,059297	2,526312
DE	-0,348867	-0,107129	2,300274
DP12	-0,296100	-0,464491	1,283202
STD	0,263989	-0,417226	2,47563
LNP	0,005847	0,112979	1,908389
DA	-0,004639	-1,064288	1,872253

A comparison of the t-statistics of the firm-specific style factor before and after the risk-adjustment process yields the results in Table 6.7 above. An initial observation is that all 25 firm-specific attributes, which were found to be significant in the unadjusted 'Full Data' regression, are still significant after the risk-adjustment process. Within the 25 significant factors at a 5% level, the absolute difference between unadjusted and risk-adjusted t-statistics is between 0% and 17%, with a mean of 1% and a median of 1%. This indicates that the market risk *Beta* does not have a material effect on the style-factor t-statistics, and therefore does not significantly impact the significance of the style attributes.

When analysing the *Beta* t-statistics resulting from the two-factor regression, it is clear that 14 of the 44 factors are significant at a 5% level. *Beta* is therefore rewarded to some extent when regressed in addition to the firm-specific factor, but the existence of *Beta* does not materially affect the significance of the style factors.

Overall, the difference in the significance of unadjusted and risk-adjusted returns has a t-statistic value of -0,09; almost completely insignificant. Therefore based on the coefficient analysis and significance analysis one can conclude in agreement with empirical evidence from van Ransburg and Robertson (2003), Janari (2003) and Acres (2007), that the addition of a market risk factor does not yield significantly different results when tested on a global scale. Style effects are present independently of the market risk factor.

6.3.3. Cumulative Monthly Payoff to Style Factors

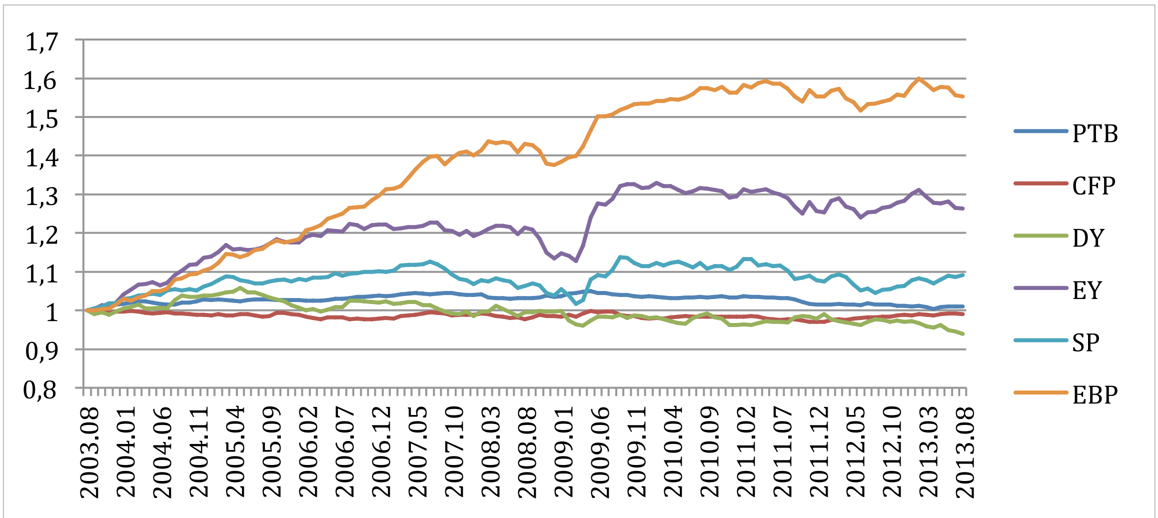
Using the Fama-MacBeth coefficient results displayed in Table 6.1, the cumulative monthly payoffs were calculated for all of the sector-specific attributes, in an equally weighted portfolio, in order to illustrate their relative behaviour over time, and express their wealth creation capacity graphically. Special note is taken of the behaviour during the U.S. credit crisis and consequent recessionary period starting in 2008. The attributes are grouped according to style for illustrative and comparative purposes. The cumulative monthly payoffs are analysed for Value, Growth, Momentum, Size & Liquidity, Risk, Leverage, and Emerging Market style groups. The evolution of the cumulative payoffs to each of the firm-specific attributes is displayed in Appendix J, along with a list of the overall cumulative payoffs in Appendix K.

6.3.3.1. Value

The value effect is analysed in Figure 6.1 below through the cumulative payoff to the factors underlying the value style. Based on the definition and empirical behaviour of value factors, one would expect the value effect to have a positive payoff in recessionary times, and an overall positive payoff over time.

Figure 6.1: Cumulative Monthly Payoff to the VALUE effect

The graph below combines the cumulative monthly payoff slopes of the value factors, namely the Price-to-Book ratio, the Cash-flow-to-Price ratio, the Dividend Yield, the Earnings Yield, the Sales-to-Price ratio and the EBITDA-to-Price ratio. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



The Fama-MacBeth results displayed in Table 6.1 show that only the EBITDA-to-Price (EBP) factor is significant, while the 'Full Data' unadjusted results displayed in Table 6.2 show that the EBITDA-to-Price (EBP), Earnings Yield (EY), Sales-to-Price (SP) and Dividend Yield (DY) are significant attributes within the value style group.

The first general observation from the cumulative value payoff analysis is the large 'dip' in the payoffs from August 2008 to August 2009. This time-period is the in line with the U.S. credit crisis and subsequent recession, which had an extensive negative effect on the global market. The steep line from August 2003 until August 2008 indicates that the payoffs to stocks with a high EBITDA-to-Price are substantial. This period is followed by a large recessionary dip, and then a positive yet somewhat insubstantial recovery from August 2008 to August 2013. The value effect is expected to perform well during recessionary times, so the dip over this period is surprising, but can be attributed to the sheer magnitude of the recession on a global scale, and is far less severe than that experienced by other style factors.

The cumulative payoff analysis indicates that the EBITDA-to-Price has a cumulative payoff of 55% over the 121-month period. This particular factor has a very strong significance when tested using both the Fama-MacBeth and 'Full Data' methods. Although never expressly tested before, this value factor seems to have significant explanatory power and should be investigated as the primary value ratio for predicting equity returns, especially in a global sample.

Earnings Yield has a cumulative payoff of 26% over the 121-month period. This Earnings-to-Price ratio also has significance when tested with the 'Full Data' regression. This finding is in line with that of Basu (1977, 1983), Ball (1978) and Reinganum (1981) who all documented significant Earnings Yield effects. Sales-to-Price also has significant explanatory power, with a cumulative payoff of 9% over the 121-month period.

Although Dividend Yield is a significant firm-specific attribute within the style group, it has a negative cumulative payoff over the 121-month period under review. Litzenberger and Ramaswamy (1979), Blume (1980), Keim (1985) and Fama and French (1988b) also find significant Dividend Yield effects, but in the opposite direction. It appears that the greater the Dividend relative to the Price of the share, the poorer the expected returns on a global scale. It is also surprising that neither the Price-to-Book Value per share (PTB), nor Cash Flow-to-Price (CFP) is found to be significant using either method. It is also worth noting that in both cases, their cumulative payoffs are negligible. These results contrast the literature of Fama and French (1992) who document a significant Book-to-Market value effect. The contradictions in this study could be the result of the inherent 'averaging' across the different markets, as individual markets could contain significant value effects, which are then reduced to insignificant when all individual markets are combined into the global market. Michaud (1999) confirms this when he concludes that individual factors have different levels of significance within different markets, and there tend to be different factors found to be significant in each market.

6.3.3.2. Growth

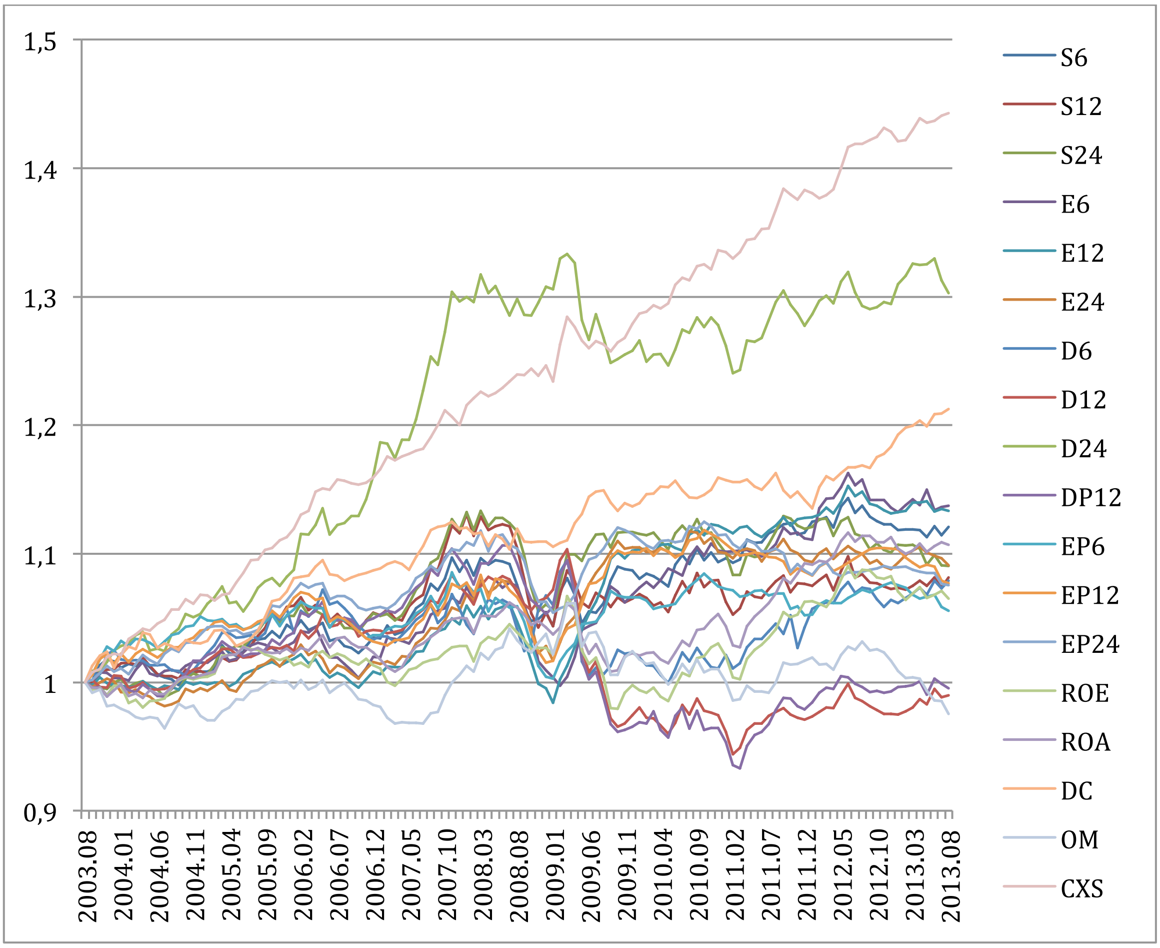
The growth effect is analysed in Figure 6.2 below through the cumulative payoff to the factors underlying the growth style. Based on the definition and empirical behaviour of growth factors, one would expect the growth effect to have a significantly negative payoff in recessionary times, and an overall payoff, that while still positive, is underwhelming and well below the payoff to value stocks.. Hodnett and Hsieh (2012b) explain that growth stocks can be equated to 'glamour' stocks, and tend to achieve lower returns than expected when predicted by the CAPM.

The payout ratio (PR) and Sales-to-Total Assets (STA) factors have been left off this graph, as they display inverse behaviour to the other growth factors and are therefore not directly comparable from a cumulative perspective. PR is the direct inverse to the Dividend Cover (DC), which is displayed in the graph below, and STA is represented in the CAPEX-to-Sales (CXS) factor, as there is a high correlation between the two.

The Fama-MacBeth results displayed in Table 6.1 show that only the Sales-to-Total Assets (STA), CAPEX-to-Sales (CXS), Dividend Cover (DC), 24-month growth in Dividend (D24) and Payout Ratio (PR) are significant, while the 'Full Data' unadjusted results displayed in Table 6.2 show that thirteen significant attributes exist within the growth style group.

Figure 6.2: Cumulative Monthly Payoff to the GROWTH effect

The graph below combines the cumulative monthly payoff slopes of the growth factors, namely the growth in Sales, growth in Earnings, growth in Dividends, 12-month growth in Dividend relative to Price, growth in Earnings relative to Price, Return on Equity, Return on Assets, Dividend Cover, Operating Margin, and CAPEX-to-Sales. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



While not as high as the cumulative payoffs from the value effect, the growth effect appears also to have an overall positive payoff. For the most part the growth factors display the same dip from August 2008 when the U.S. credit crisis recession hit the markets, but otherwise grew relatively consistently over the period. It does however appear that the Operating Margin (OM), 12-month growth in Dividends (D12), and 12-month growth in Dividend relative to Price (DP12) factors were not able to recover from this recessionary dip and ended the period yielding net negative returns. It is interesting to note that while the 6-month growth in Dividends (D6), 12-month growth in Dividends (D12) and 24-month growth in Dividends (D24) factors are very highly correlated and all represent growth in Dividends, they have very different payoff patterns. This could be due to the fact that Dividends are usually only announced once a year, and therefore a 2-year period captures the growth in Dividend best.

The CAPEX-to-Sales (CXS) factor and D24 factor definitely stand out as being both significant and having high cumulative payoffs of 44% and 30% respectively. These findings are in line with those of Ahmed and Nanda (2001) who reveal that firms with growth prospects tend to outperform on a risk-adjusted basis over time.

6.3.3.3. Momentum

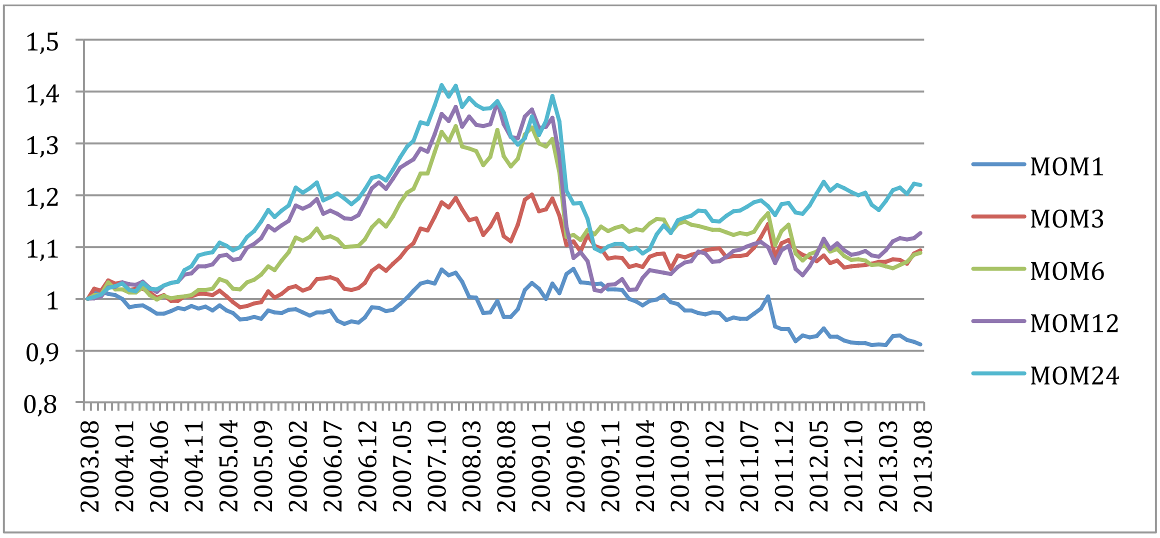
The momentum effect is analysed in Figure 6.3 below through the cumulative payoff to the factors underlying the momentum style. Based on the definition and empirical behaviour of momentum factors, one would expect a recessionary period to have a significantly negative effect on the momentum payoff, as negative momentum as a result of the recession would be expected to endure for a period of time.

The momentum effect can be split into a short-term one-month momentum, and a medium-to-long term momentum effect comprising 3-month, 6-month, 12-month and 24-month momentum.

While none of the momentum factors are found to be significant under the Fama-MacBeth methodology, the 'Full Data' unadjusted results displayed in Table 6.2 shows that all of the momentum factors, except the six-month momentum, are found to be significant at a 5% level.

Figure 6.3: Cumulative Monthly Payoff to the MOMENTUM effect

The graph below combines the cumulative monthly payoff slopes of the momentum factors, namely the 1-month momentum, 3-month momentum, 6-month momentum, 12-month momentum, and 24-month momentum. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



From Figure 6.3 above it is clear that the medium-to-long-term momentum: three, six, twelve, and twenty-four-month prior return (MOM3, MOM6, MOM12, and MOM24), all have significant positive payoffs over the 121-month period. MOM24 produces the greatest payoff, followed by MOM12, MOM3, and MOM6. The significant medium-to-long-term momentum attributes have a fairly consistent payoff over the period from August 2003 to January 2009, after which, as expected, the recessionary applies sharp downward pressure to the payoffs. Thereafter there is a gradual rebound in cumulative payoff until the end of the sample period. The momentum factors therefore seem to contradict the weak-form market efficiency theories, and should be acknowledged as powerful predictors of equity returns. These findings are in line with that of Bernard and Thomas (1990), who found that there are medium-to-long-term inertia patterns in stock returns, and Jegadeesh and Titman (1993), who noted a similar situation when they buy 'winner' and sell 'loser' portfolios constructed on the performance of shares for the prior six months.

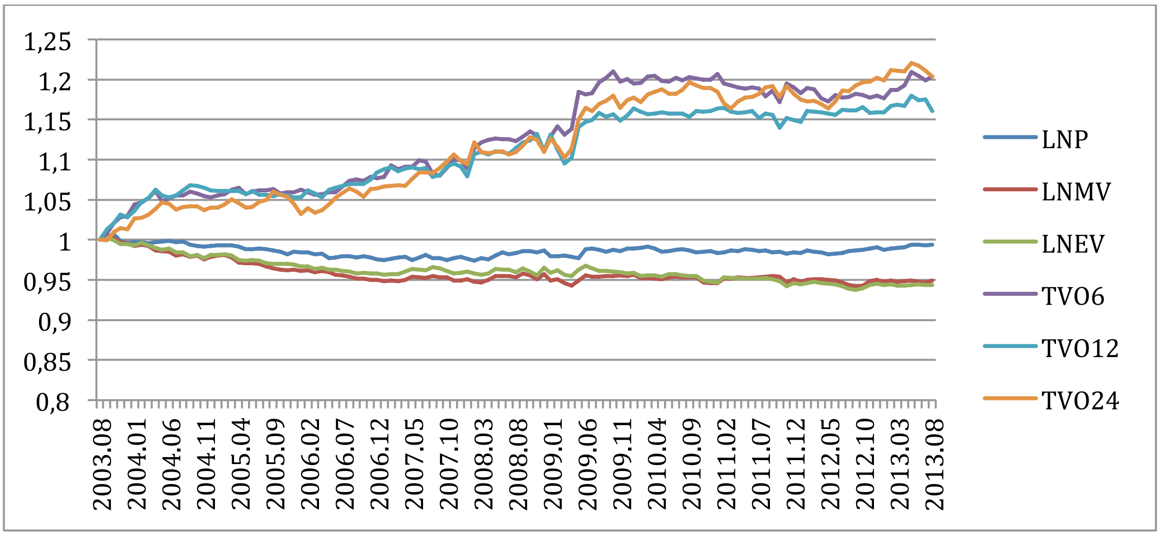
It is interesting to note that the short-term one-month prior return (MOM1) has a negative payoff over the 121-month period. This is in line with short-term reversals linked to empirical results of overreaction by the market, and speaks to market irrationality. Jegadeesh and Titman (1992) also found evidence of this short-term momentum effect, and these monthly return reversals have been included in the Carhart (1997) 4-factor model and successfully capture the short-term momentum style anomaly found on the U.S. stock market.

6.3.3.4. Size and Liquidity

The size and liquidity effect is analysed in Figure 6.4 below through the cumulative payoff to the factors underlying the size and liquidity style. Based on the definition and empirical behaviour of these size factors, one would expect a recessionary period to have a significantly negative effect on the cumulative payoff, as smaller, riskier companies with less liquidity will be hit harder by a global market downturn.

Figure 6.4: Cumulative Monthly Payoff to the SIZE & LIQUIDITY effect

The graph below combines the cumulative monthly payoff slopes for the size and liquidity factors, namely the log of Price, the log of Market Value, the log of Enterprise Value, the 6-month growth in Turnover by Volume, the 12-month growth in Turnover by Volume, and the 24-month growth in Turnover by Volume. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



The Fama-MacBeth results displayed in Table 6.1 show that only the 24-month growth in Turnover by Volume (TVO24) and 6-month growth in Turnover by Volume (TVO6) are significant, while the 'Full Data' unadjusted results displayed in Table 6.2 show that all three liquidity factors, TVO6, TVO12 and TVO24, are significant at the 5% level. Neither method finds any of the size factors to be significant.

From Figure 6.4 above it is clear that the liquidity factors: TVO6, TVO12 and TVO24, all have significant positive payoffs over the 121-month period. This implies that there is a strong return rewarded for liquid shares, as they appear to be less risky and are easier to trade in and include in a portfolio. This is a contradiction of the Haugen and Baker (1996) finding, as they find that stocks with high, growing levels of trading volume are more expensive and therefore produce lower levels of expected returns. It is, however, in agreement with the findings of Serra (2002) that the average payoffs of liquidity factors are positive in emerging markets.

The negative payoff displayed for the size factors is in line with empirical research and indicates the negative relationship between size and returns, as smaller companies tend to have higher returns than larger companies. It is surprising, however, that the size style group does not display any significant attributes, either by the 'Full Data' method or the Fama-MacBeth method. This is contradictory to the empirical findings of Banz (1981), Reinganum (1981), Basu (1983), Chan and Chen (1991), and Fama and French (1992), who all identify a small-firm size effect. In line with the findings of Fama and French (1996) who find a very weak size effect, the cumulative payoff analysis above indicates that the effect seems to have disappeared during this period. This is in agreement with the findings of Serra (2002) who finds no evidence of a size effect in emerging market economies.

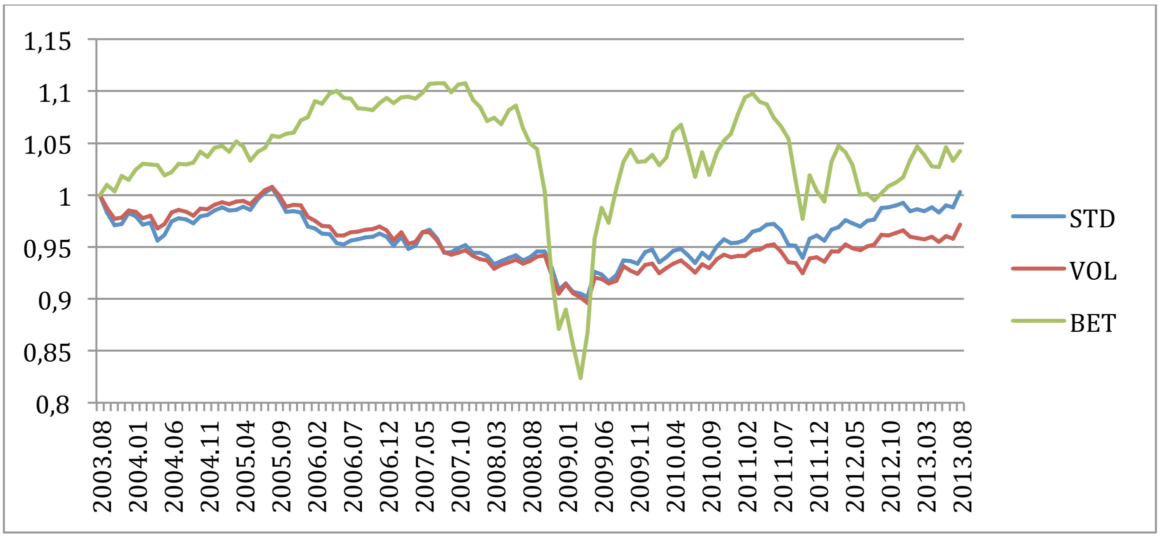
6.3.3.5. Risk

The risk effect is analysed in Figure 6.5 below through the cumulative payoff to the factors underlying the risk style. Based on the definition and empirical behaviour of these risk factors, one would expect a recessionary period to have a significantly negative effect on the cumulative payoff, as riskier companies will be hit harder by a global market downturn. It should be noted that Fama and French (1992) found that

Beta possesses almost no explanatory power over the 1963 to 1990 period.

Figure 6.5: Cumulative Monthly Payoff to the RISK effect

The graph below combines the cumulative monthly payoff slopes for the risk factors, namely the Standard Deviation of returns, the Volatility of returns, and the *Beta* of the stocks. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



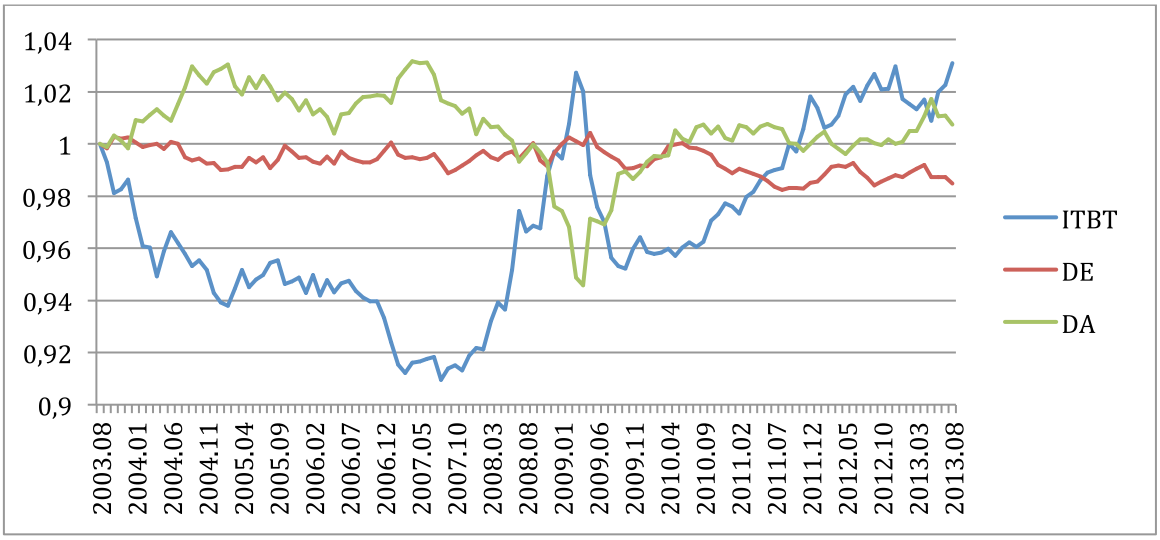
The risk style group comprises the Standard Deviation of returns (STD), Volatility of returns (VOL), and market risk *Beta* (BET) associated with each stock. All of these factors are found to be insignificant using both the Fama-MacBeth and the 'Full Data' regression methods, and seem to have a very small cumulative payoff over the 121-month period. STD and BET display slightly positive payoffs, while VOL displays a slightly negative payoff. The *Beta* factor does exhibit the expected dip during the recessionary period, however the overall finding that risk factors are not significant is contradictory to the Markowitz (1952) risk-return framework, which predicts a significant negative relationship between the sector returns and the risk measure.

6.3.3.6. Leverage

The leverage effect is analysed in Figure 6.6 below through the cumulative payoff to the factors underlying the leverage style. The leverage effect can be associated with an increased level of risk, which should, in accordance with empirical finding, bring with it a positive payoff.

Figure 6.6: Cumulative Monthly Payoff to the LEVERAGE effect

The graph below combines the cumulative monthly payoff slopes for the leverage factors, namely the Interest Cover before Tax, the Debt-to-Equity Ratio and the Debt-to-Assets ratio. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



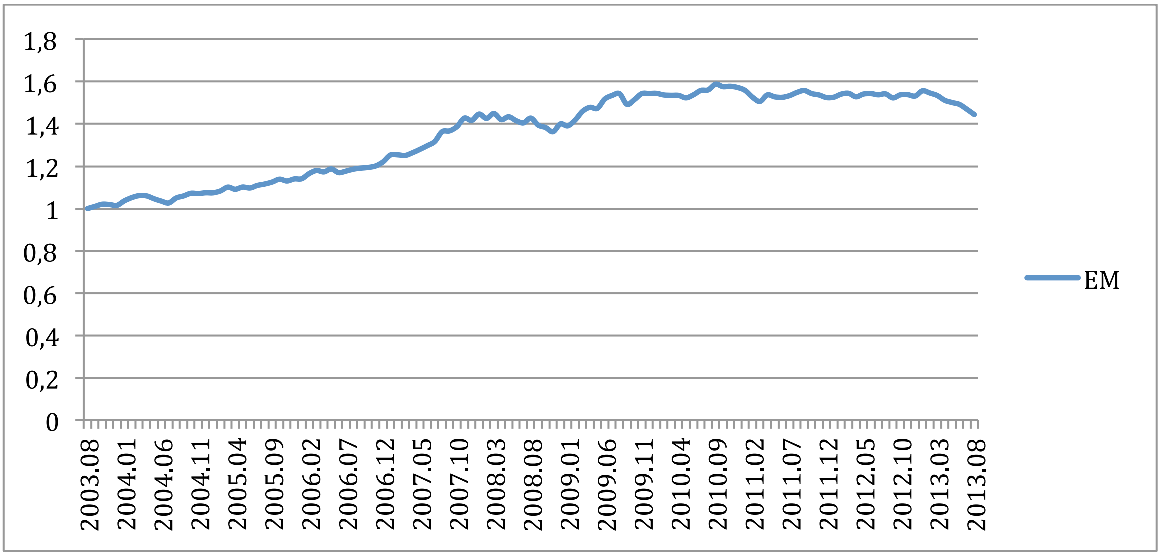
The leverage style group comprises the Interest Cover before Tax (ITBT), Debt-to-Equity ratio (DE), and Debt-to-Assets ratio (DA) for each stock. All of these factors are found to be insignificant using both the Fama-MacBeth and the 'Full Data' regression methods, and seem to have a very small cumulative payoff over the 121-month period. Despite being remarkably volatile over the period, the ITBT does provide a positive payoff of 4% during the period, the DA an even smaller 0.3%, and the DE provides a negative 4% payoff. What is noteworthy from the above graph is the behavior of the ITBT variable which appears to yield significantly negative returns over periods where the economic conditions are favourable, but reverts to generating positive returns the moment that the market dips. This plays on an element of behavioural investing whereby investors place a great deal of value on cash reserves to meet debt obligations during uncertain times, but penalize stocks for holding reserves during good economic conditions. These results contradict those of Bhandari (1988), who finds a significantly positive relationship between leverage and average return.

6.3.3.7. Emerging Market

The emerging market effect is analysed in Figure 6.7 below through the cumulative payoff to the factors underlying the emerging market style. The emerging market effect can be associated with an increased level of risk, decreased liquidity of the share, and decreased share size, which should bring with it a positive payoff over time.

Figure 6.7: Cumulative Monthly Payoff to the EMERGING MARKET effect

The graph below combines the cumulative monthly payoff slopes of the emerging market factor. The cumulative slopes were calculated from the monthly Fama-MacBeth slopes, which are calculated as the coefficient when regressing the firm-specific factors against the forward returns for each of the top 1468 stocks in the global market. The cumulative monthly payoff is displayed for the 121-month period from August 2003 to August 2013.



The emerging market (EM) factor has been found to be very significant under both the Fama-MacBeth and 'Full Data' regression methods. EM also exhibits a significantly positive cumulative payoff of 44% over the testing period, and seems to have a fairly stable slope progression. There appears to be a slight dip over the recessionary period, and a rather slow recovery, but no significant volatility otherwise. It is clear therefore that Emerging Market stocks are rewarded for their access to growth, increased risk, and value potential. The Emerging Market factor is vital to understanding global returns.

6.3.4. Correlation coefficients

The 44 attributes considered in this study were chosen and constructed in order to test a comprehensive list of firm-specific style factors. It can therefore be expected that some of the payoffs will exhibit similar behaviour, and may even be highly correlated. Correlation matrices were used to identify pairs of highly correlated attributes. Correlation coefficients are calculated for every pair of factors throughout the period using the unadjusted time series of payoffs to the respective factors as calculated using the Fama-MacBeth regression method.

For the purpose of this analysis, a pair of attributes with a correlation coefficient greater than 0.7 or less than -0.7 is considered as having a high degree of correlation. No attributes are excluded from the analysis and multi-factor model for high correlation, but highly correlated significant factors are highlighted in the correlation matrix below in Table 6.8. Correlation matrices for each of the styles are displayed in Appendix L.

Table 6.8: Correlation Matrix for Significant Attributes using Unadjusted Returns

The table shows the Pearson correlations between the time series of monthly payoffs to those firm-specific attributes, which are significant using the Fama MacBeth regression method over the period from August 2003 to August 2013. The attributes exhibit at least a 5% level of significance in the OLS cross-sectional regression tests on the unadjusted returns data. Attribute pairs with a high degree of correlation (greater than 0.7 or less than -0.7) are presented in grey. Correlations were calculated in *E-Views*.

	STA	CXS	EBP	DC	EM	D24	TVO24	TVO6	PR
STA	1								
CXS	-0,703	1							
EBP	0,2052	-0,257	1						
DC	-0,12	0,0554	0,2483	1					
EM	-0,416	0,3164	0,3795	0,4195	1				
D24	-0,443	0,4118	0,135	0,2516	0,6623	1			
TVO24	0,1758	-0,197	0,3951	0,0687	-0,002	-0,122	1		
TVO6	0,2101	-0,151	0,3281	0,0296	-0,121	-0,136	0,6458	1	
PR	-0,08	0,0588	-0,244	-0,497	0,0718	0,1053	-0,197	-0,264	1

6.4. Multivariate Results

After the data points were prepared, the univariate analysis was conducted, and the behaviour of factors was analysed, the procedure outlined in Section 5.4 was followed in order to investigate the multivariate relationship between firm-specific style attributes and unadjusted forward returns, and construct a characteristic-based model of the cross-section of worldwide returns. All attributes were considered in this analysis, including those that were found to be insignificant at the 5% level in the univariate regression tests, and including the factors that were highly correlated with one another, in order to construct the most robust multi-factor model possible.

The aim of this Section is to assess the payoffs to the individual firm-specific style attributes in a multifactor setting, and construct a multi-factor forecasting model that can forecast returns successfully.

6.4.1. Stepwise Construction

The stepwise optimal model is derived through a stepwise procedure, which uses the univariate 'Full Data' OLS regression slope t-statistics to establish the order in which the factors are tested and added, and the 'Full Data' method OLS regression coefficients' t-statistics and Adjusted R-squared results as the primary criterion for assessing the model at each step.

In following the forward stepwise process outlined in Section 5.4.1, a 15-factor model was constructed in which each of the 15 factors is significant at a 5% level, and the Adjusted R-squared is at a maximum. The process of adding variables is presented in Table 6.9 below, and the Adjusted R-squared for the multi-factor model is illustrated as each significant factor is added in Figure 6.8.

Table 6.9: Forward Stepwise Multi-Factor Regression Process

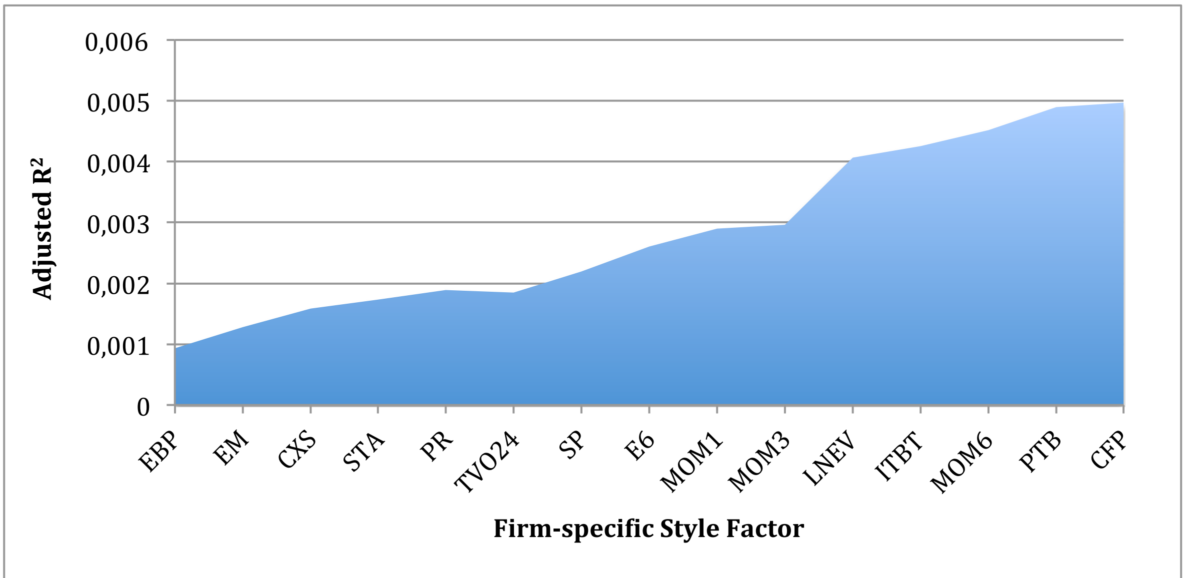
This process was followed when deciding on the optimal factor to add to the model at each stage. As each factor is added, the t-stat of every factor in the new model is checked for significance. If the added factor is not significant within the multi-factor model, or forces another factor to become insignificant, it is taken out and the next factor is added. If, however, the added factor is significant within the model and all existing factors retain their significance then the factor is permanently added. Throughout the process the Adjusted R-squared should be increasing. The factors that are retained in the model are highlighted in grey, and R-squared and Adjusted R-squared for the model at each point are given.

Stepwise Factors	Factor Added	R2	Adjusted R2
1	**EBP**	**0,000935**	**0,000928**
2	**EM**	**0,001291**	**0,001278**
3	**CXS**	**0,001603**	**0,001581**
4	**STA**	**0,001766**	**0,001732**
5a	EY	0,00241	0,002365
5b	DC	0,002274	0,002226
5c	**PR**	**0,001933**	**0,001889**
6a	MOM24	0,001916	0,001861
6b	D24	0,001782	0,001717
6c	**TVO24**	**0,001907**	**0,001846**
7a	TVO6	0,001741	0,001664
7b	TVO12	0,001714	0,00164
7c	S6	0,001853	0,001781
7d	MOM12	0,001889	0,001816
7e	**SP**	**0,002267**	**0,002194**
8	**E6**	**0,002693**	**0,002605**
9	**MOM1**	**0,002995**	**0,002896**
10a	E24	0,002942	0,00283
10b	S24	0,002766	0,002653
10c	S12	0,002982	0,002871
10d	D6	0,002645	0,002516
10e	DY	0,003054	0,002943
10f	**MOM3**	**0,00307**	**0,002959**
11a	ROE	0,003092	0,002969
11b	BET	0,003095	0,002972
11c	EP24	0,002868	0,002722
11d	**LNEV**	**0,0042**	**0,00407**
12	**ITBT**	**0,004407**	**0,004259**
13a	EP12	0,004119	0,003938
13b	LNMV	0,00441	0,004249
13c	**MOM6**	**0,004677**	**0,004516**
14	**PTB**	**0,005073**	**0,004899**
15a	OM	0,005076	0,00489
15b	D12	0,00462	0,004399
15c	**CFP**	**0,005154**	**0,004967**

15d	EP6	0,005063	0,004863
15e	VOL	0,00496	0,004599
15f	DE	0,005096	0,004908
15g	DP12	0,004713	0,004489
15h	STD	0,00496	0,004599
15i	LNP	0,005091	0,004905
15j	DA	0,005103	0,004916

Figure 6.8: Forward Stepwise Adjusted R-squared

The Adjusted R-squared is the key metric in deciding whether an added factor adds to the significance of the overall mulit-factor model. The Adjusted R-squared is a measure of the amount of explained variation in the model, accounting for the number of factors added and provides an indication of whether an added factor adds significantly to the overall effectiveness of the model. With each added factor, the Adjusted R-squared should be strictly increasing and the model is deemed complete once the Adjusted R-squared reaches a maximum.



It appears that the decision as to which factors to retain in the model is directly linked to the correlation between the factors, which makes sense as one would expect only one of a highly correlated pair to be significant within a multi-factor model as the addition of the other would decrease the significance of both. This allows for a balanced multi-style-factor model to be created.

6.4.2. Optimal Model

The forward optimal stepwise regression process yields a multi-factor model including 15 style factors, with six different styles represented: Value, Growth, Momentum, Size and Liquidity, Leverage, and Emerging Market. Each of the 15 factors is significant at a 5% level, and the overall Adjusted R^2 is 0.5%. The optimal multivariate regression output is displayed in Figure 6.9 below.

Figure 6.9: Optimal Multi-factor Regression Output

A forward stepwise regression method was followed in order to construct a characteristic-based model of the cross-section of worldwise returns. The multivariate regression output displays the fifteen firm-specific factors that comprise the optimal multi-variate model with the highest Adjusted R-squared. It is clear that all factors have a significant payoff at a 5% level, as all absolute t-statistics are above 2. All factors have been standardised to facilitate direct comparison, indicated by the 'S' at the beginning of each variable name.

Dependent Variable: RET
Method: Panel Least Squares
Date: 11/26/13 Time: 14:24
Sample: 2003M08 2013M08
Periods included: 121
Cross-sections included: 1288
Total panel (unbalanced) observations: 79700

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016146	0.000336	47.98858	0.0000
SEBP	0.003032	0.000459	6.610857	0.0000
SEM	0.001239	0.000358	3.459410	0.0005
SCXS	0.002555	0.000475	5.382065	0.0000
SSTA	-0.004235	0.000406	-10.42952	0.0000
SPR	-0.000901	0.000339	-2.656793	0.0079
STVO24	0.001342	0.000369	3.635603	0.0003
SSP	0.003641	0.000434	8.391150	0.0000
SE6	0.001706	0.000590	2.894209	0.0038
SMOM1	-0.002768	0.000441	-6.280379	0.0000
SMOM3	0.003058	0.000551	5.552658	0.0000
SLNEV	-0.003708	0.000404	-9.183949	0.0000
SITBT	0.001658	0.000400	4.147175	0.0000
SMOM6	-0.002715	0.000515	-5.269480	0.0000
SPTB	-0.001655	0.000394	-4.195630	0.0000
SCFP	-0.000933	0.000426	-2.189072	0.0286

R-squared	0.005154	Mean dependent var	0.014950
Adjusted R-squared	0.004967	S.D. dependent var	0.092276
S.E. of regression	0.092047	Akaike info criterion	-1.932841
Sum squared resid	675.1303	Schwarz criterion	-1.930976
Log likelihood	77039.70	Hannan-Quinn criter.	-1.932269
F-statistic	27.52262	Durbin-Watson stat	1.868137
Prob(F-statistic)	0.000000		

6.4.3. Individual Factor Payoff Analysis in Multi-factor Setting

The forward stepwise regression procedure has revealed the behaviour of significant and insignificant style factors when analysed in a multivariate setting. It is interesting to note how some significant factors have become even more significant, some insignificant factors have become significant, and many significant factors are no longer significant in the presence of other factors. It is clear that the relationships and dynamics between factors result in different levels of significance when firm-specific style factors are analysed in isolation or in a multi-factor setting. Table 6.10 below shows the factors in the optimal multi-factor model, and the discrepancies between their significance in the multivariate vs. univariate settings.

Table 6.10: Factor Significance in Univariate vs. Multivariate Setting

The optimal multi-factor style model contains 15 factors from 6 different style groupings. These factors are displayed along with their individual t-statistics calculated in a univariate setting using the 'Full Data' regression method. The univariate t-statistics can be compared to the t-statistics associated with the same factors within the multivariate setting. All factors were standardised, allowing for direct comparison.

Factor	Multivariate t-stat	Univariate ('Full Data') t-stat
EBP	**6.610857**	12,01632
EM	**3.459410**	10,07539
CXS	**5.382065**	8,697826
STA	**-10.42952**	-8,638352
PR	**-2.656793**	-5,811374
TVO24	**3.635603**	4,917646
SP	**8.391150**	3,136522
E6	**2.894209**	3,134748
MOM1	**-6.280379**	-2,794372
MOM3	**5.552658**	2,769465
LNEV	**-9.183949**	-1,502681
ITBT	**4.147175**	1,412397
MOM6	**-5.269480**	0,839988
PTB	**-4.195630**	-0,807364
CFP	**-2.189072**	-0,569354

Of the 44 firm-specific factors tested, and the 25 factors found to be significant using the 'Full Data' univariate regression method, the 15 factors above were found to be significant within a multivariate setting. There are 10 factors that can be classified as robust, as they exist both in and out of competition with other variables, namely EBP, EM, CXS, STA, PR, TVO24, SP, E6, MOM1 and MOM3. The remaining 15 factors, which were found to be significant in the 'Full Data' univariate regression results, can therefore be deemed less robust as they fail to retain their significance in a multivariate setting. The last 5 factors within the optimal multi-factor model: LNEV, ITBT, MOM6, PTB, and CFP, have gained significance in a multivariate setting, as they were found to be insignificant in the univariate results.

6.5. Summary and Conclusion

Results of both the univariate and multivariate analysis provide indisputable evidence in support of Hypothesis 1: style effects are significant at a 5% level on a global scale. In a univariate setting there are 25 firm-specific style factors that have a significant return payoff, specifically the Value, Growth, Momentum, Emerging Market and Size / Liquidity style groupings. These style factors have the ability to explain deviations in expected return, and have significant predictive power.

A *Beta*-adjustment, through a two-factor regression of each factor with the relevant *Beta*, reveals that *Beta* does not have a significant effect on the payoff to the significant factors revealed in the univariate analysis. The market-risk factor is also not found to have a significant payoff within the univariate setting. Hypothesis 2 is thus confirmed in that any predictability of global asset returns from style characteristics is not due to risk and does not dissipate after adjustment for risk. It must be noted, however, that the method of calculation for the *Datastream Beta* factor is a key factor in this result.

The most robust style effect is the Emerging Market effect, which has a consistent and significant payoff over the full period with limited volatility. As can be expected, the leverage and risk effects are heavily affected by recessionary periods, yet rebound without too much deviation from the expected trajectory. The size and liquidity effect and value effect are negatively affected by recessionary periods, but also show steady recovery thereafter. The momentum and growth factors appear to be the most affected by recessionary periods, and while some factors within those styles are able to weather recessionary periods, overall the volatility is high and recovery slow. Hypothesis 3 cannot be definitively answered as the different styles experience different reactions to recessionary periods and time series. It can be concluded that the patterns and relationships between returns and style factors are complex, and change significantly over time.

A multivariate analysis revealed that out of the 25 significant factors in a univariate setting, 10 remained significant at a 5% level in a multivariate setting. And an additional 5 factors gained significance within a multivariate setting. Therefore Hypothesis 4 is confirmed in that style effects exist both independently, in a univariate setting, and in a multi-factor model. This multi-factor model can then be used as a predictor of returns in an asset-pricing model. Hypothesis 5, that style effects are significant predictors of returns within a multi-factor model, can only be confirmed after substantial testing is conducted on the model.

Therefore, from the results of this study it is clear that the existence of significant style characteristics has value beyond the mere disproval of the CAPM, as they can be used as proxies for unobservable risk, and in this way can and should be included in a multi-factor asset-pricing model.

-7-

Summary and Conclusion

"In the end, I think we can hope for a coherent story that (1) relates the cross-section properties of expected returns to the variation of expected returns through time, and (2) relates the behavior of expected returns to the real economy in a rather detailed way. Or we can hope to convince ourselves that no such story is possible."

- Fama (1991; p1610)

7.1. Introduction

The objectives of this study are outlined in the first Chapter, and all relate to the relationship between stock returns and firm-specific style attributes in a global setting. These objectives are summarized below.

Firstly, to investigate the relationship between global stock returns and firm-specific attributes, both before and after risk adjustment. Secondly, to investigate the univariate behaviour of the payoffs to the firm-specific attributes in terms of consistency and significance, varying market conditions, and robustness to varying time periods.

Thirdly, to derive a multi-factor forecasting and asset-pricing model. The existence of significant and persistent style characteristics has value beyond the mere disproval of the CAPM, as they can be used as proxies for unobservable risk, and in this way can be included in asset pricing models. This is directly linked to the fourth objective: to investigate the behaviour of the payoffs to the firm-specific attributes within a multivariate setting, where only the most robust factors retain significance.

Within the context of the first four objectives, the fifth objective is to test the level of global market efficiency, specifically the weak-form efficient market hypothesis. If firm-specific factors have explanatory power or forecasting ability, this shows either a misspecification of the asset-pricing model, or an inefficient market, or both.

The final objective is to enhance the existing empirical literature by testing previously untested firm-specific factors on a previously untested sample of 1468 global stocks; and testing more than just the anomalous factors found to be significant in prior research, therefore not only adding to evidence on existing factors but also considering the possibility of other attributes also having explanatory value.

Section 7.2 summarises the results of this study in terms of the objectives and hypotheses listed in the first Chapter. Section 7.3 proceeds to suggest possible extensions to this research and topic, and Section 7.4 concludes the analysis.

7.2. Summary of Results

The dataset used in this analysis is made up of two parts: the total returns for each share, and the firm-specific factors representing different styles. The data is collected monthly over a thirteen-year period, from August 2000 to August 2013. The analysis is only conducted on the 121-month period from August 2003 to August 2013, however, the preceding data is required for growth and momentum calculations.

The biases that have the potential to impact this study include: data-snooping, which is addressed by using a very large global sample that has not been the subject of many tests before, a combination of new and tested firm-specific factors, and a current time-period that not been tested in the same way before; look-ahead bias, which is addressed through the use of *Datastream* whose information is only updated once it becomes public knowledge; non-uniformity and comparability between all stocks and style factors, which is facilitated through the use of a common currency, the U.S. Dollar, and the standardisation of all factors; and survivorship bias, which will still affect the results as the firms included in the sample are only those that have survived the sample period.

The sample used to capture the global market comprises the top 1500 global shares based on their market value. The dataset is then smoothed so as to only include the 1468 most consistent and liquid shares. The data is adjusted for outliers both manually and through a 'winsorisation' procedure, and all firm-specific factors are standardised to allow for comparability between the regression coefficients.

In response to the first objective, a significant relationship was discovered between global forward stock returns and firm-specific style factors before risk-adjustment. Twenty-five firm-specific attributes are significant at the 5% level under the 'Full Data' methodology. These include: EBITDA to Share Price (EBP), Emerging Market (EM), CAPEX to Sales (CXS), Sales to Total Assets (STA), Earnings Yield (EY), Payout Ratio (PR), Dividend Cover (DC), 24-month prior return (MOM24), 24-month growth in Dividends (D24), 24-month, 12-month, and 6-month growth in Turnover by Volume (TVO24, TVO12, TVO6), 6-month growth in Sales (S6), 12-month prior return (MOM12), Sales to Share Price (SP), 6-month growth in Earnings (E6), Return on Assets (ROA), 12-month growth in Earnings (E12), 1-month prior return (MOM1), 24-month growth in Earnings (E24), 3-month prior return (MOM3), 24-month growth in Sales (S24), 12-month growth in Sales (S12), 6-month growth in Dividends (D6), and Dividend Yield (DY). Value, Growth, Momentum, Size & Liquidity, and Emerging Market styles are all represented in this sample.

Of these twenty-five factors, nine are also significant at the 5% level using the Fama-MacBeth methodology. These include: Sales to Total Assets (STA), CAPEX to Sales (CXS), EBITDA to Share Price (EBP), Dividend Cover (DC), Emerging Market (EM), 24-month growth in Dividends (D24), 24-month and 6-month growth in Turnover by Volume (TVO24, TVO6), and Payout Ratio (PR). These nine attributes are significant across both methods of testing and are therefore considered to be robust. The same Value, Growth, Momentum, Size & Liquidity, and Emerging Market styles are represented here as using the 'Full Data' approach.

In addition to these unadjusted results, a significant relationship was discovered between global forward stock returns and firm-specific style factors after risk-adjustment. The factors identified as significant above, retain their significance when *Beta* is included in the model. A *Beta*-adjustment, through a two-factor regression of each factor with the relevant *Beta*, reveals that *Beta* does not have a significant effect on the payoff to the significant factors revealed in the univariate analysis. In addition, the market-risk factor has an insignificant payoff within the univariate setting. Any predictability of global asset returns from style characteristics does not dissipate after adjustment for risk. Therefore, firm-specific attributes are able to explain the variation in global returns above and beyond the ability of the market risk factor.

In response to the second objective, a cumulative payoff analysis indicates that the EBP factor has by far the highest cumulative payoff of 55% over the 121-month period, and EY has a cumulative payoff of 26%. These value payoffs, along with the SP factor with a cumulative payoff of 9% over the period, are by far the highest payoffs tested and indicate the explanatory and forecasting power and of the Value effects. From a Growth anomaly perspective, the CXS factor and D24 factor stand out as being both significant and having high cumulative payoffs of 44% and 30% respectively. The remaining growth factors have cumulative payoffs of between 0% and 21%. The medium-to-long-term momentum factors have cumulative payoffs between 9% and 22%, while the short-term one-month momentum factor has a negative cumulative payoff of 9%. Liquidity payoffs are between 16% and 20%, while size payoffs are significantly less at between 1% and 6%. The EM factor exhibits a significantly positive cumulative payoff of 44% over the testing period, and seems to have a fairly stable slope progression. Overall, the univariate firm-specific factors exhibit volatility in their payoffs during significant changes in market conditions; as was evidenced during the 2008-2009 crisis, but remain robust to varying time periods.

In response to the third objective, a multi-factor model was constructed to have maximum explanatory power using multiple style factors. Of the 44 firm-specific factors tested, 15 factors were found to be significant within an optimal multivariate setting. In descending order of significance, these are: EBITDA to Share Price (EBP), Emerging Market (EM), CAPEX to Sales (CXS), Sales to Total Assets (STA), Payout Ratio (PR), 24-month growth in Turnover by Volume (TVO24), Sales to Share Price (SP), 6-month growth in Earnings (E6), 1-month prior return (MOM1), 3-month prior return (MOM3), natural log of Enterprise Value (LNEV), Interest Cover before Tax (ITBT), 6-month prior return (MOM6), Share Price to Book Value per Share (PTB), and Cash Flow to Price (CFP). The combination of these factors yields an Adjusted R-squared value of 0,005, and represents the Value, Growth, Momentum, Size & Liquidity, Emerging Market, and Leverage effects. As an extension of this research, the constructed multi-factor model would need to be tested using a unique control sample.

In response to the fourth objective, the forward stepwise regression procedure revealed the behaviour of style factors when analysed in a multivariate setting. There are 10 factors that can be classified as robust, as they are significant both in and out of competition with other variables, namely: EBP, EM, CXS, STA, PR, TVO24, SP, E6, MOM1 and MOM3. These 10 variables had significant payoffs in both the univariate and multivariate tests. Of the 25 factors that were found to be significant in the 'Full Data' univariate regression, the remaining 15 factors can therefore be deemed less robust as they fail to retain their significance in a multivariate setting. The additional 5 factors within the optimal multi-factor model: LNEV, ITBT, MOM6, PTB, and CFP, have gained significance in a multivariate setting, as they were found to be insignificant in the univariate results. It is clear that the relationships and dynamics between factors result in different levels of significance when firm-specific style factors are analysed in isolation or in a multi-factor setting.

As far as the fifth objective goes, the results from the univariate and multivariate analysis provide evidence for the existence of style anomalies on the global stock market. This infers that firm-specific style factors have explanatory power and forecasting ability, and shows either a misspecification of the classic asset-pricing model, or an inefficient global market, or both.

In response to the final objective, this study has tested both previously-tested and previously-untested firm-specific style factors, on a previously-untested sample of 1468 global shares. Many new factors were found to be significant, like Emerging Market, EBITDA to Share Price, and CAPEX to Sales, which can be used to redefine the existing style models. It is a hope that this research can be continued, and the models tested further, with the ultimate goal of using the identified style factors to predict global returns and construct global portfolios.

7.3. Suggestions for Extension

The sheer size of the data used to represent the global market: a panel of 44 factors from 1468 shares tested over a 121-month period, required compromises to be made in terms of the practicality and accuracy of the analysis. While all care and consideration was taken to ensure possible bias was dealt with effectively, a survivorship bias is still prevalent in these tests. This could potentially be addressed through a new analysis method that takes into account the shares that have de-listed over the period.

In terms of the calculations of factors used for testing, improvements could be made to the currency conversion method and calculation of market *Beta*. Due to the vast number of currencies involved in the analysis, all data was converted into U.S. Dollar currency using

Datastream before it was analysed. This process of currency conversion should be controlled better, as it is unclear which exchange rate was used by *Datastream*, or if the currency conversion occurred using the spot rates throughout the period or using the current spot rate applied backwards in time. A more controlled currency conversion could produce more accurate results. The *Beta* for this analysis was also drawn from *Datastream* for each of the 1468 stocks and at the end of each month. *Datastream* calculated these *Beta*s as the sensitivities to each share's domestic index. As previous empirical research concluded that the risk-adjustment of returns didn't have a significant effect on the payoffs to style factors, the *Beta*s sufficed for this analysis. However, further testing should be done using *Betas* that are estimated for each firm against a global market index proxy.

Further style anomalies should be tested on a global scale, especially the well-documented January Effect, and the seasonality and timing for each of the significant firm-specific factors should be considered. Rozeff and Kinney (1976) provide the first conclusive evidence of seasonality in stock returns in their study of NYSE common stock data from 1904 to 1974 as they find that there are statistically significant differences in monthly returns, primarily because of large January returns. Keim (1983) finds that in the period from 1963 to 1979, up to fifty percent of the significant size effect is attributable to abnormally high returns in the month of January. Jaffe, Keim and Westerfield (1989) use rigorous tests and a larger sample period from 1951 to 1986 and find significant P/E and size effects, but also find that only the P/E effect is significant when the month of January is controlled for. Testing the existence of a January effect, as well as controlling for the potential January effect in the testing of other style factors, is a suggestion for extension of this study.

The additional testing of style anomalies using different methodologies would strengthen the results in this analysis and improve the overall understanding of style anomalies within the context of a global market. The multi-factor model in this analysis is constructed using the forward stepwise regression process. Additional or improved methods used to construct the multi-factor model, investigate the relationship between factors, investigate the behaviour of the univariate factors, and investigate the existence and significance of the style anomalies are suggested extensions. Economic analysis on each of the significant firm-specific factors, and an investigation of the life cycle for each of the style factors should be conducted in order to shed light on the empirical findings so as to better understand their behaviour and the reasons for their existence.

7.4. Conclusion

The construction and testing of asset-pricing models continues to be a central theme in global finance. An understanding of mean-variance analysis developed into the stringent Capital Asset Pricing Model (CAPM) and many more comprehensive multi-factor asset-pricing models over the years. The CAPM specifically has molded the way academics and practitioners think about risk and average returns. The most recent angle to this asset-pricing story, however, is the existence of 'anomalous' factors, which indicate that the CAPM doesn't adequately describe returns. This study has adopted a global perspective in the testing for anomalous firm-specific style attributes in global returns, using the top 1468 stocks over the period August 2003 to August 2013.

A key to understanding the results of this study is to understand the underlying relationships that exist between each of the individual economies that make up the global market. While particular style anomalies are significant in some markets, they may be subsumed by other effects that are more robust. Therefore the empirical results from the United States and other independent markets need to be understood in the context of a global market.

Style anomalies are found to exist at a firm level on a global scale, as firm-specific attributes are able to add to the explanation of the cross-section of returns in a worldwide setting. The specific style groups containing significant firm-specific attributes are the Value, Growth, Momentum, Size and Liquidity, Leverage, and Emerging Market groupings. Ten factors within these style groupings are considered robust in their explanation of expected return variation, as they exist in both a univariate and multivariate setting. The behaviour of, and relationships between the firm-specific style factors give great insight into the payoffs to investing in different style factors over time, and is key to the construction of a multi-factor model. The firm-specific style factors that remain significant in a multivariate setting became the core of a multi-factor style model, which can be used to explain a degree of the unexplained returns, predict returns, understand the global market behaviour and price global assets for use within a global portfolio.

This study adds to the substantial body of theoretical and empirical work on asset pricing, which has been complicated in recent times by the existence of anomalies within individual markets, and the growing popularity of global investing and diversification. The results of this study will have a significant impact on the understanding of the global stock market, and the use of style factors to explain the cross-section of returns with the goal of constructing a universally accepted multi-factor asset pricing model for global equities.

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APPENDIX

Appendix A: Country Code Key

The 1468 stocks used in this analysis have their primary listing in 53 different countries. The country codes and associated country names are listed below.

Code	Country
US	United States
JP	Japan
CN	China
GB	Great Britain
CA	Canada
FR	France
HK	Hong Kong
DE	Germany
AU	Australia
BR	Brazil
KR	South Korea
CH	Switzerland
SE	Sweden
IN	India
NL	Netherlands
RU	Russia
SG	Singapore
MX	Mexico
TW	Taiwan
ES	Spain
MY	Malaysia
IT	Italy
SA	Saudi Arabia
ZA	South Africa
TH	Thailand
TR	Turkey
NO	Norway
BE	Belgium
ID	Indonesia
CL	Chile
CO	Colombia
DK	Denmark
PL	Poland
FI	Finland
IE	Ireland
PH	Philippines
QA	Qatar
AT	Austria
KW	Kuwait
PT	Portugal
CZ	Czech Republic
GR	Greece
IL	Israel
LU	Luxembourg
MA	Morocco
NZ	New Zealand
AR	Argentina
EG	Egypt
HR	Croatia
HU	Hungary
PK	Pakistan
RO	Romania
VE	Venezuela

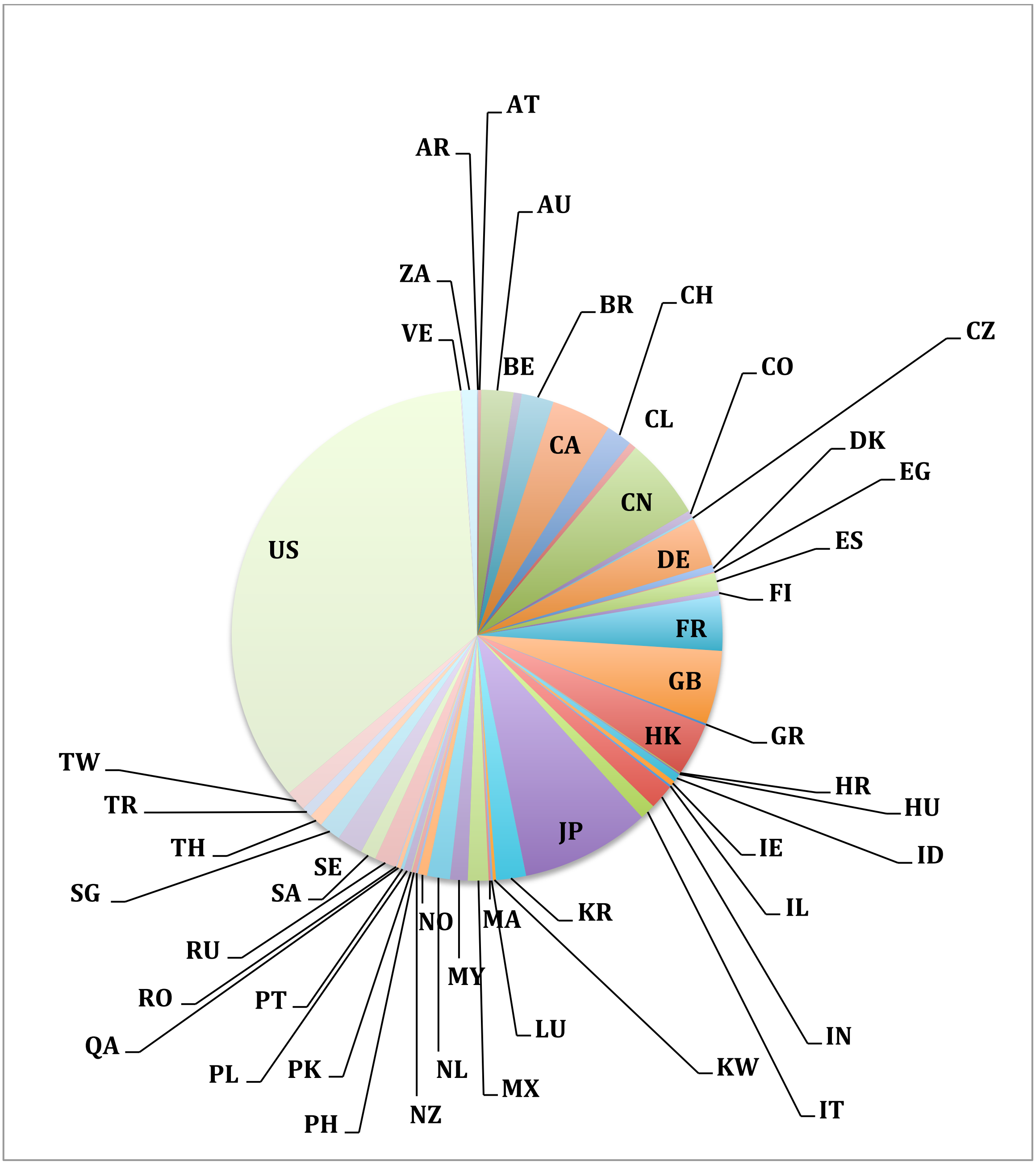
Appendix B: MV of Stocks by Country

The table shows the distribution of stocks in the global top 1468 shares based on the Market Value of the stocks from each country that are included in the analysis. The countries are ordered by total Market Value in descending order.

Country	US $million
US	16289661,24
JP	2569317,45
GB	2451093,77
CN	2012318,15
FR	1513119,62
HK	1465444,96
DE	1308407,17
CA	1229151,87
CH	925131,37
AU	872158,09
BR	662219,74
KR	621156
NL	581520,52
RU	560320,79
ES	475938,65
IN	463050,33
SE	448820,22
SG	426775,65
TW	359463,31
IT	329798,07
MX	328156,56
SA	265089,25
ZA	246344,21
BE	229612,01
MY	229243,24
NO	189226,96
TH	163844,77
DK	162339,98
ID	152822,88
CO	143341,33
CL	116695,6
TR	103897,98
IE	88100,81
QA	83149,83
FI	82702,34
PL	78234,1
IL	44796,2
PH	41547,52
AT	36181,05
PT	36025,88
KW	34058,99
LU	26859,4
NZ	20810,39
CZ	20566,59
GR	19501,07
MA	16817,93
VE	15070,54
PK	10377,3
AR	10336,63
HU	7397,51
RO	7330,82
EG	7293,47
HR	7181,2

Appendix C: Visual Representation of Countries - Proportioned by the Number of Stocks

The distribution of stocks in the global top 1468 based on the number of stocks from each country that are included in the series is shown below. There are 53 countries represented in the top 1468 global shares based on Market Value. 27 or these countries are defined as 'Emerging' and 26 are defined as 'Developed'. The most notable countries are the 514 stocks from the US, 125 stocks from Japan, 79 stocks from China and 71 stocks from Great Britain.



Appendix D: Complete Distribution of Stocks based on Industries

The distribution of stocks in the global top 1468 based on the number of stocks from each industry that are included in the series is shown below. The Market Value of the stocks from each industry is also displayed.

Industry	#	MV $ million
Banks	154	5383209,14
Integrated Oil & Gas	42	2533473,39
Pharmaceuticals	39	2021537,08
Mobile Telecom.	42	1320538,52
Exploration & Prod.	52	1061462,22
Automobiles	25	934878,76
Divers. Industrials	23	853434,85
Computer Hardware	11	838346,63
Fixed Line Telecom.	23	813467,41
Broadcast & Entertain	31	799114,97
Life Insurance	36	793469,91
Software	18	735402,6
Food Products	38	721395,24
Con. Electricity	43	706444,62
Broadline Retailers	15	669028,44
Semiconductors	26	636764,42
Commodity Chemicals	21	571566
Tobacco	11	528797,67
Internet	9	514572,77
Brewers	13	473322,56
Real Estate Hold, Dev	29	443817,12
General Mining	10	443751,41
Specialty Chemicals	24	433887,8
Industrial Machinery	27	422534,14
Biotechnology	15	419869,85
Soft Drinks	12	402237,37
Clothing & Accessory	17	395142,42
Computer Services	12	391217,43
Investment Services	20	390199,72
Food Retail,Wholesale	25	377053,02
Reinsurance	7	368317,4
Oil Equip. & Services	17	358890,49
Personal Products	13	340842,42
Consumer Finance	8	337735
Comm. Vehicles,Trucks	21	335928,29
Pipelines	16	329108,76
Nondur.Household Prod	6	319291,43
Aerospace	12	318157,11

Full Line Insurance	11	316622,1
Apparel Retailers	11	310033,84
Healthcare Providers	13	303842,54
Prop. & Casualty Ins.	19	288785,48
Asset Managers	15	265846,4
Medical Equipment	16	262456,34
Multiutilities	11	257318,03
Consumer Electronics	5	253796,7
Telecom. Equipment	10	253524,95
Restaurants & Bars	8	245891,76
Auto Parts	15	241011,32
Specialty Finance	20	223252,57
Railroads	8	215558,09
Home Improvement Ret.	4	206428,42
Gambling	9	192098,41
Drug Retailers	6	185998,51
Gas Distribution	12	185058,74
Distillers & Vintners	8	184507,13
Electrical Equipment	9	182509,21
Specialty Retailers	16	180458,04
Building Mat.& Fix.	12	180249,8
Iron & Steel	12	177924,52
Business Support Svs.	12	176423,68
Electronic Equipment	11	175946,55
Nonferrous Metals	11	166437,61
Heavy Construction	16	166370,31
Travel & Tourism	8	160755,46
Defense	7	153750,88
Delivery Services	5	148979,61
Industrial Suppliers	8	147209,52
Retail REITs	11	145404,19
Specialty REITs	7	131287,02
Medical Supplies	7	116556,44
Airlines	11	107601,15
Financial Admin.	7	106408,12
Transport Services	8	95009,55
Coal	5	94290,47
Ind. & Office REITs	8	90117,26
Spec.Consumer Service	4	88823,99
Alt. Electricity	6	88455,45
Media Agencies	6	86031,33
Tires	4	82992,73
Footwear	3	78541,72
Publishing	5	77943,79
Gold Mining	6	75017,64
Hotels	8	74418,65
Dur. Household Prod.	7	68842,12

Farming & Fishing	2	62766,87
Exchange Traded Funds	5	60055,6
Elec. Office Equip.	3	59452,64
Recreational Services	4	56687,84
Toys	4	56448,58
Marine Transportation	3	51232,5
Insurance Brokers	3	50344,03
Bus.Train & Employmnt	3	42644,9
Residential REITs	3	42390,86
Waste, Disposal Svs.	3	40394,54
Plat.& Precious Metal	3	35009,95
Containers & Package	3	31413,37
Water	4	30427,91
Investment Companies	2	28100,87
Paper	2	21057,44
Home Construction	2	20130,61
Mortgage REITs	2	20071,77
Trucking	2	17490,72
Mortgage Finance	1	16918,16
Unclassified	1	16728,68
Aluminum	2	16554,1
Recreational Products	2	15221,75
Hotel & Lodging REITs	1	12773,02
Furnishings	1	8519,94
Forestry	1	7429,93
Diamonds & Gemstones	1	7309,01
Real Estate Services	1	7249,2

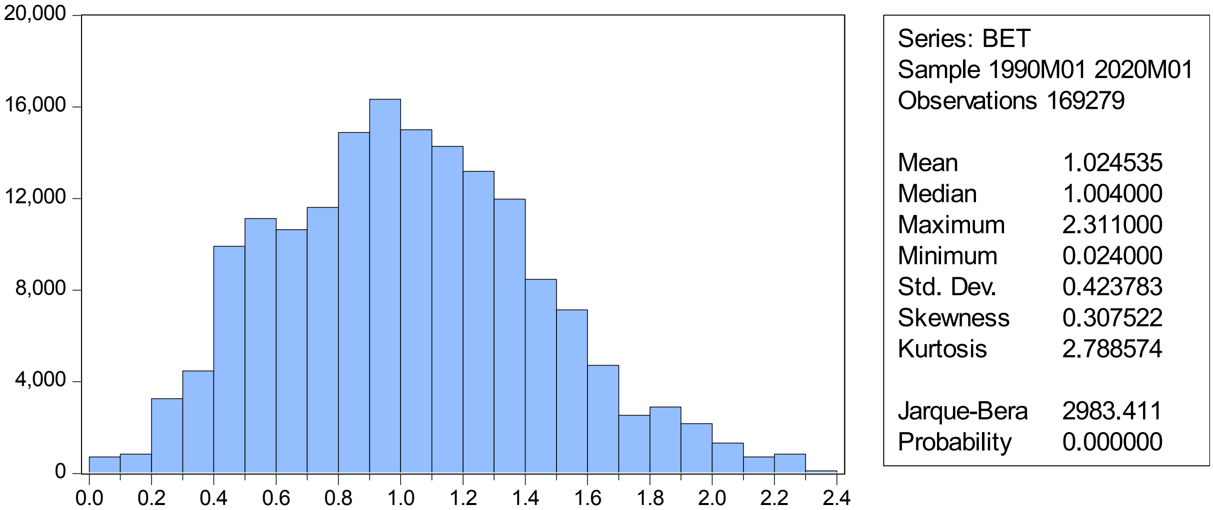
Appendix E: Countries and Classification as Emerging or Developed

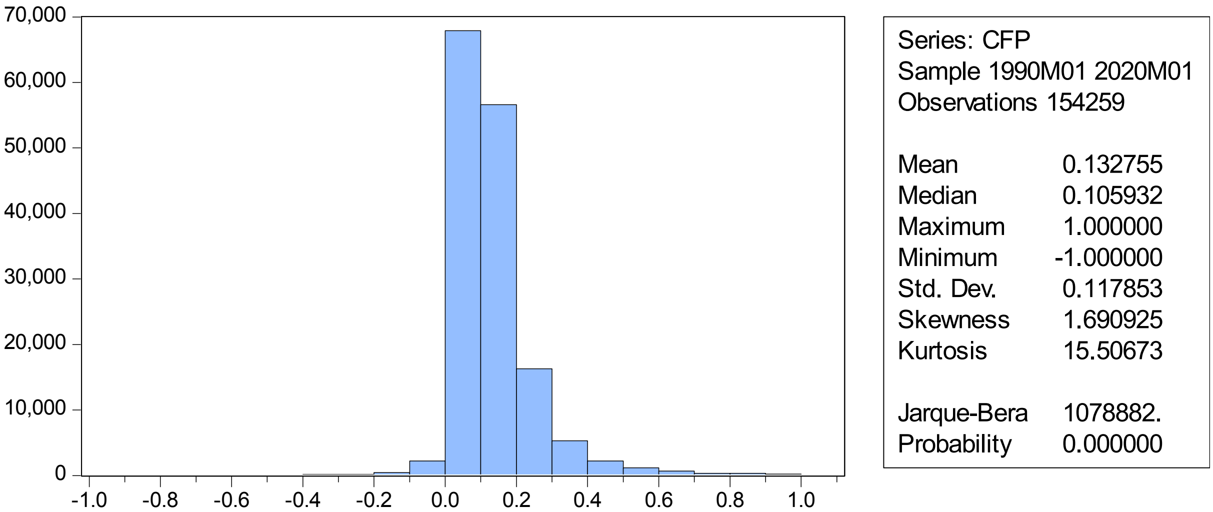
The 1468 stocks used in this analysis have their primary listing in 53 different countries, 27 of which are classified as Emerging markets and 26 of which are classified as Developed markets by the IMF. The country and classification is listed below.

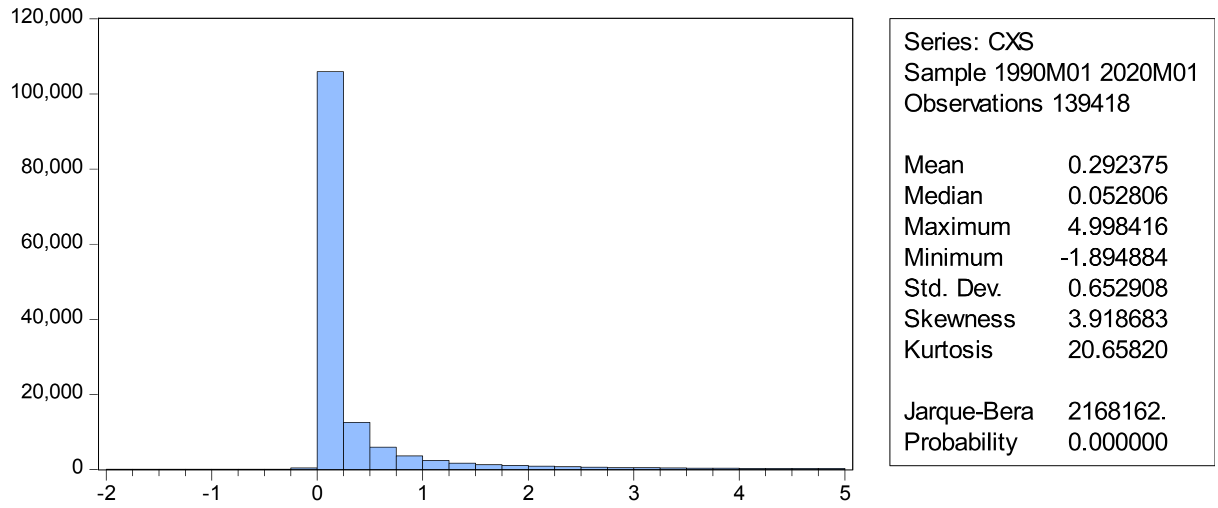
Country	Classification
Argentina	Emerging
Austria	Developed
Australia	Developed
Belgium	Developed
Brazil	Emerging
Canada	Developed
Switzerland	Developed
Chile	Emerging
China	Emerging
Colombia	Emerging
Czech Republic	Developed
Germany	Developed
Denmark	Developed
Egypt	Emerging
Spain	Developed
Finland	Developed
France	Developed
Great Britain	Developed
Greece	Developed
Hong Kong	Emerging
Croatia	Emerging
Hungary	Emerging
Indonesia	Emerging
Ireland	Developed
Israel	Developed
India	Emerging
Italy	Developed
Japan	Developed
South Korea	Developed
Kuwait	Emerging
Luxembourg	Developed
Morocco	Emerging
Mexico	Emerging
Malaysia	Emerging
Netherlands	Developed
Norway	Developed
New Zealand	Developed
Philippines	Emerging
Pakistan	Emerging
Poland	Emerging
Portugal	Developed
Qatar	Emerging
Romania	Emerging
Russia	Emerging
Saudi Arabia	Emerging
Sweden	Developed
Singapore	Developed
Thailand	Emerging
Turkey	Emerging
Taiwan	Emerging
United States	Developed
Venezuela	Emerging
South Africa	Emerging

Appendix F: Factor Histograms

These histograms represent the data series after the initial winsorisation and trimming procedures were completed. The obvious outliers were removed first, followed by a winsorisation procedure, which was then checked manually. The data as it appears in these histograms was then further manipulated in an e-Views program shown in Appendix B by trimming all data points to within three standard deviations of the mean.



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Kurtosis 20.65820
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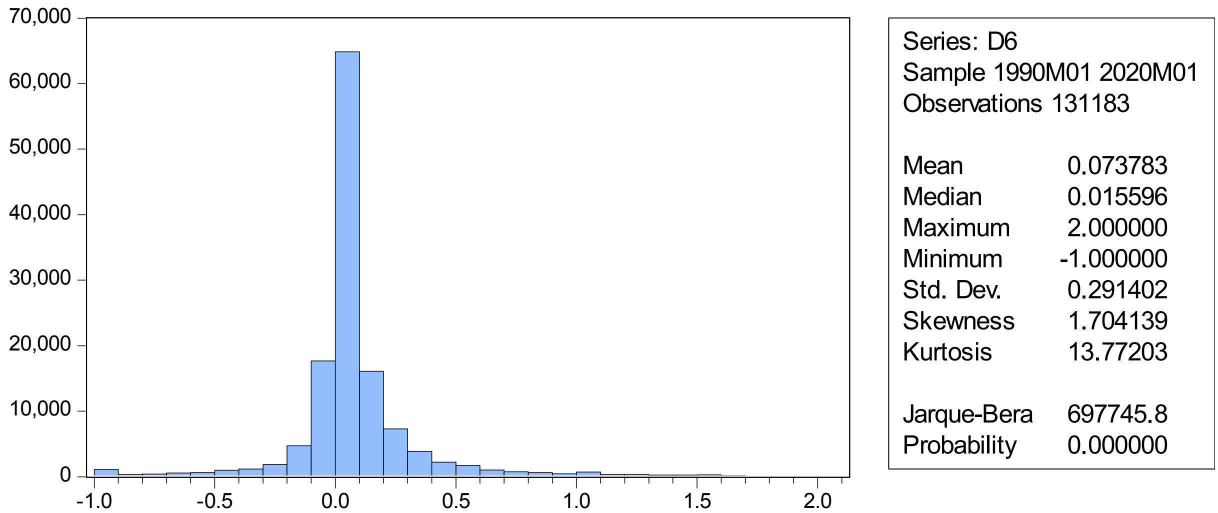
Probability 0.000000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Median 0.015596
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Kurtosis 13.77203
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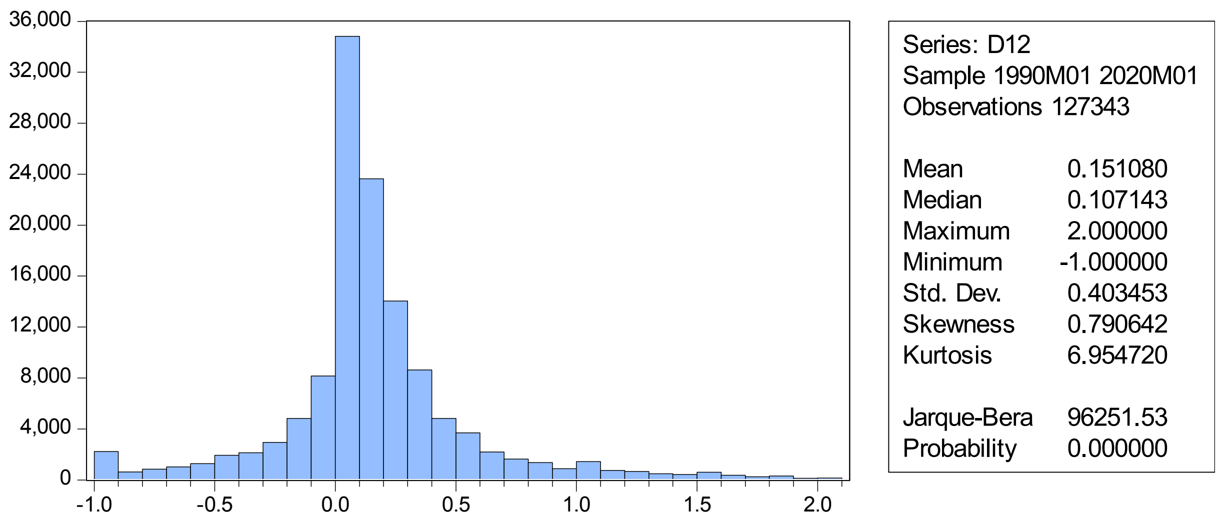
Probability 0.000000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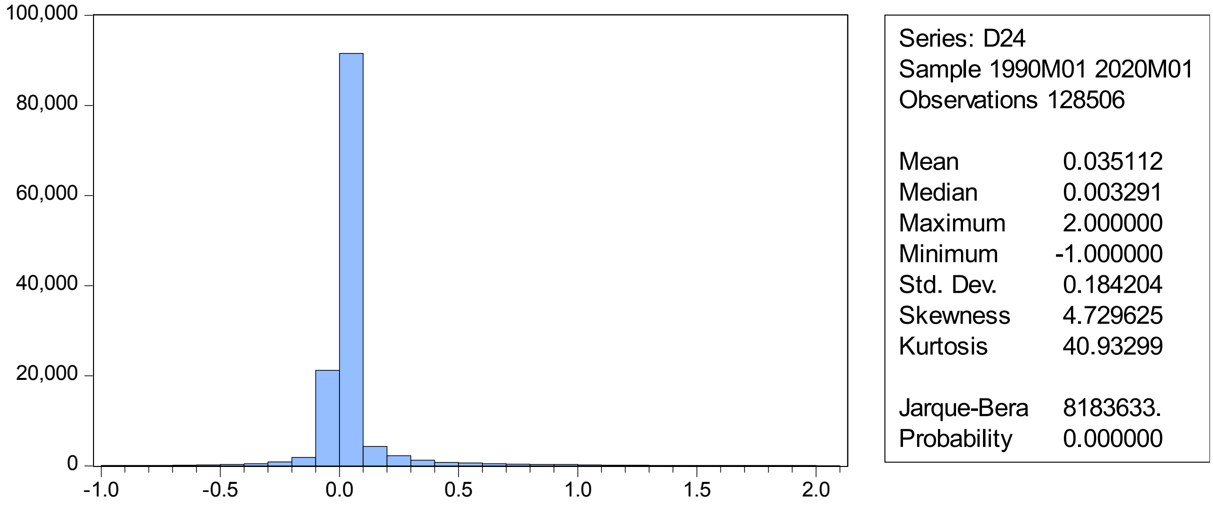
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60,000
40,000
20,000
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0.0
0.5
1.0
1.5
2.0
Series: D24
Sample 1990M01 2020M01
Observations 128506
Mean 0.035112
Median 0.003291
Maximum 2.000000
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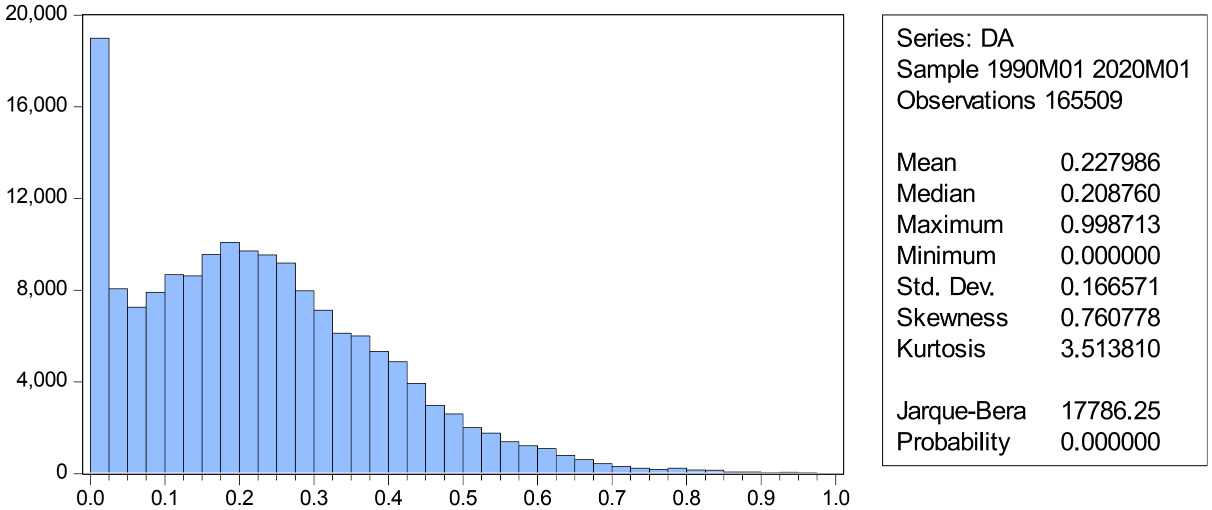
20,000
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12,000
8,000
4,000
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0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Series: DA
Sample 1990M01 2020M01
Observations 165509
Mean 0.227986
Median 0.208760
Maximum 0.998713
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Kurtosis 3.513810
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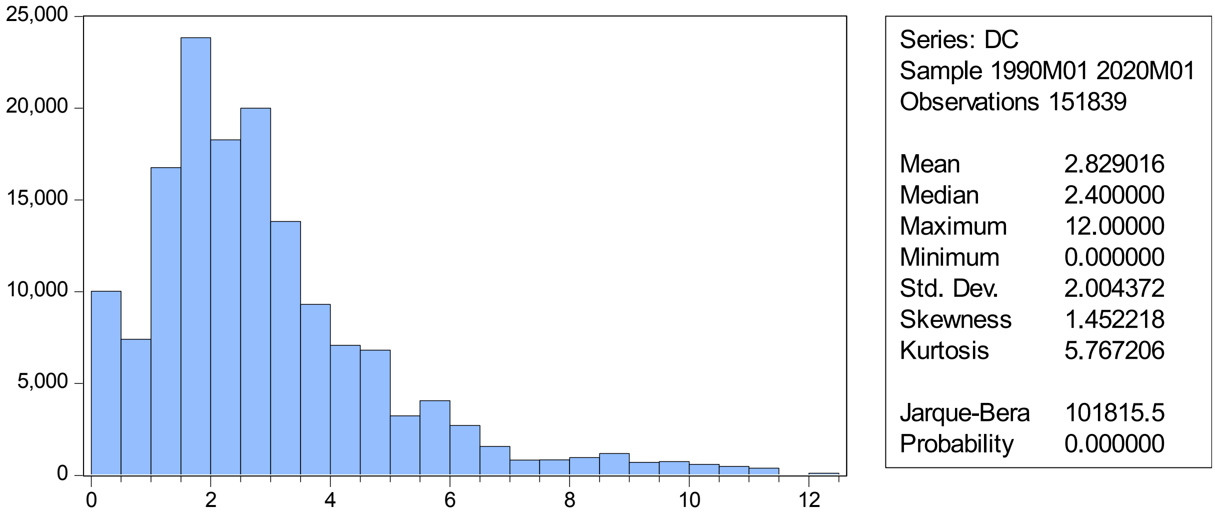
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2
4
6
8
10
12
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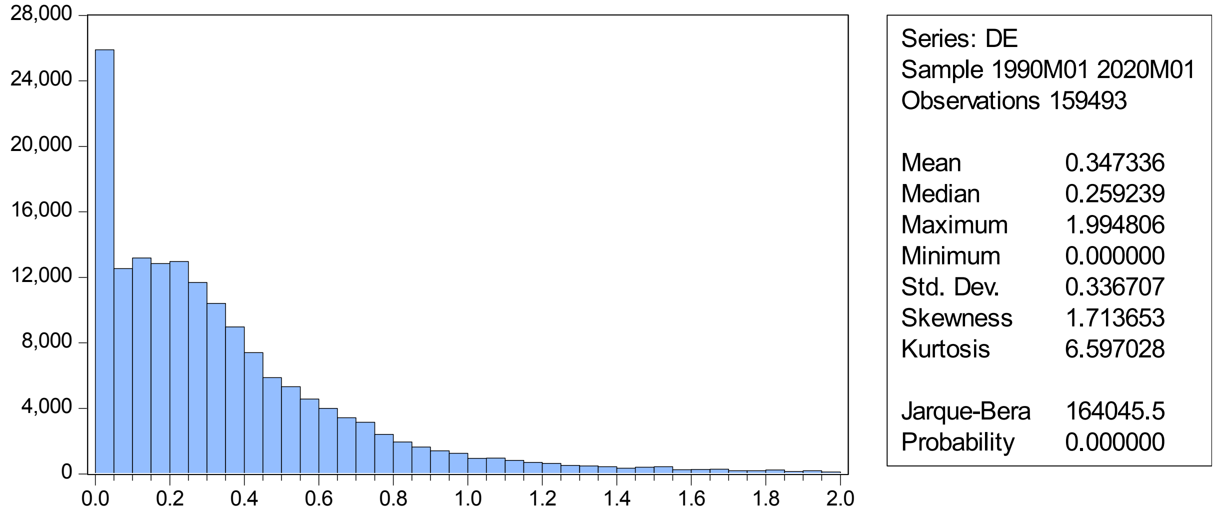
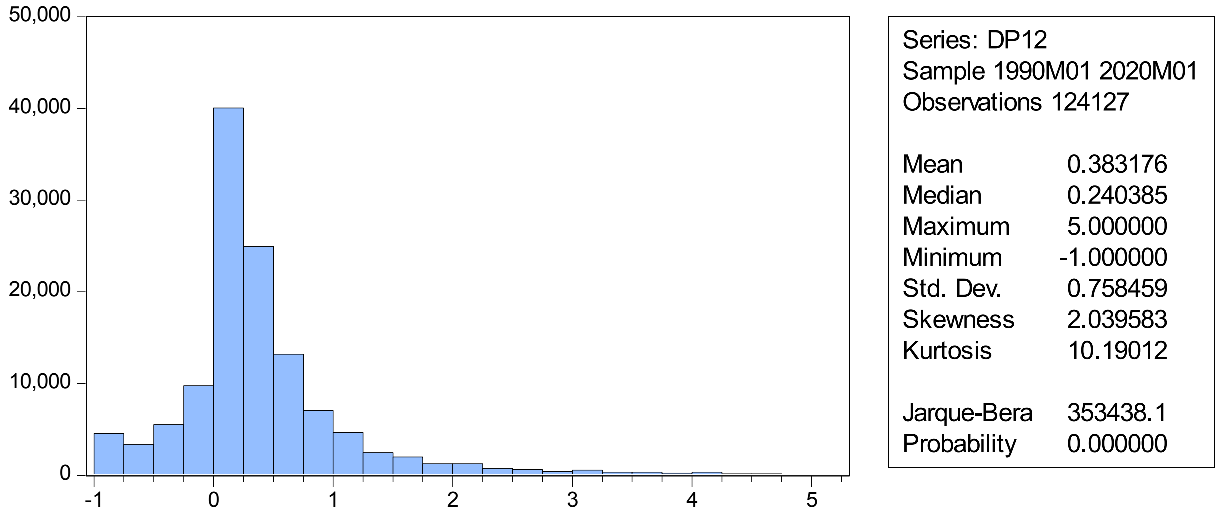
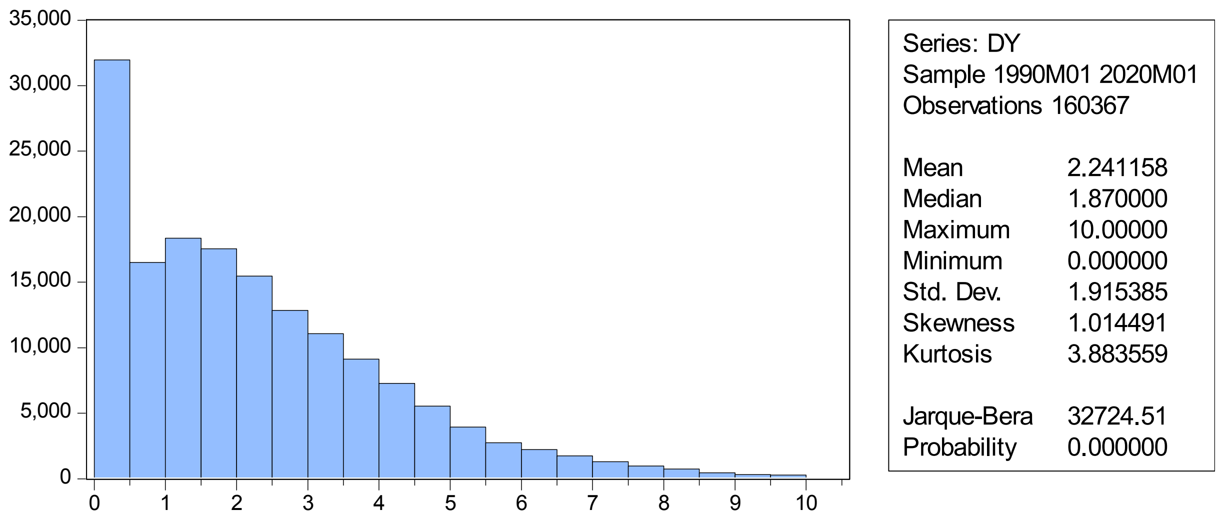
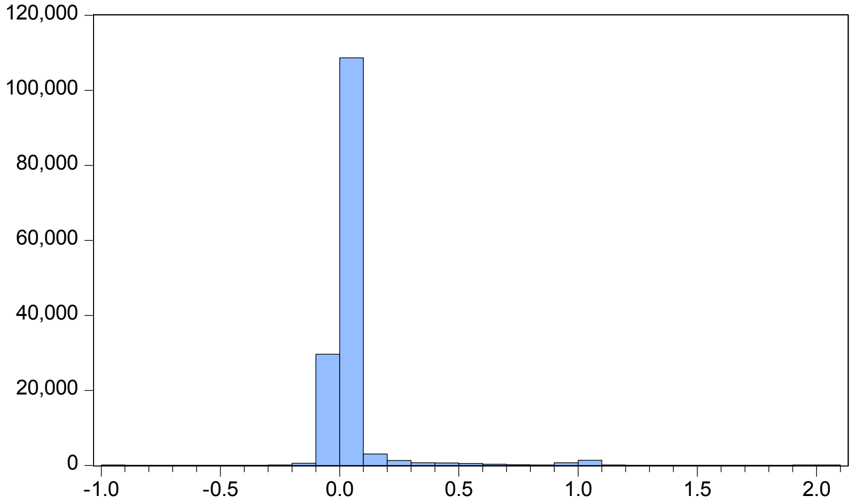
Maximum 12.00000
Minimum 0.000000
Std. Dev. 2.004372
Skewness 1.452218
Kurtosis 5.767206
Jarque-Bera 101815.5
Probability 0.000000


Series: DE
Sample 1990M01 2020M01
Observations 159493
Mean 0.347336
Median 0.259239
Maximum 1.994806
Minimum 0.000000
Std. Dev. 0.336707
Skewness 1.713653
Kurtosis 6.597028
Jarque-Bera 164045.5
Probability 0.000000

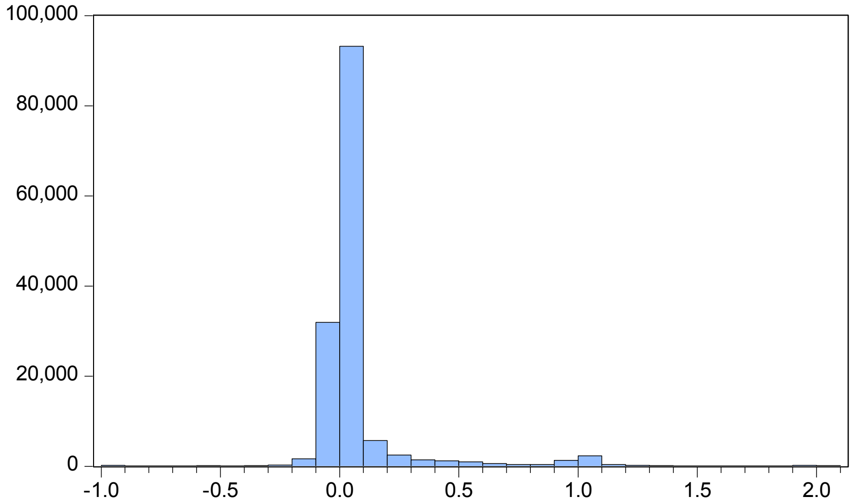

Series: DP12
Sample 1990M01 2020M01
Observations 124127
Mean 0.383176
Median 0.240385
Maximum 5.000000
Minimum -1.000000
Std. Dev. 0.758459
Skewness 2.039583
Kurtosis 10.19012
Jarque-Bera 353438.1
Probability 0.000000


Series: DY
Sample 1990M01 2020M01
Observations 160367
Mean 2.241158
Median 1.870000
Maximum 10.00000
Minimum 0.000000
Std. Dev. 1.915385
Skewness 1.014491
Kurtosis 3.883559
Jarque-Bera 32724.51
Probability 0.000000



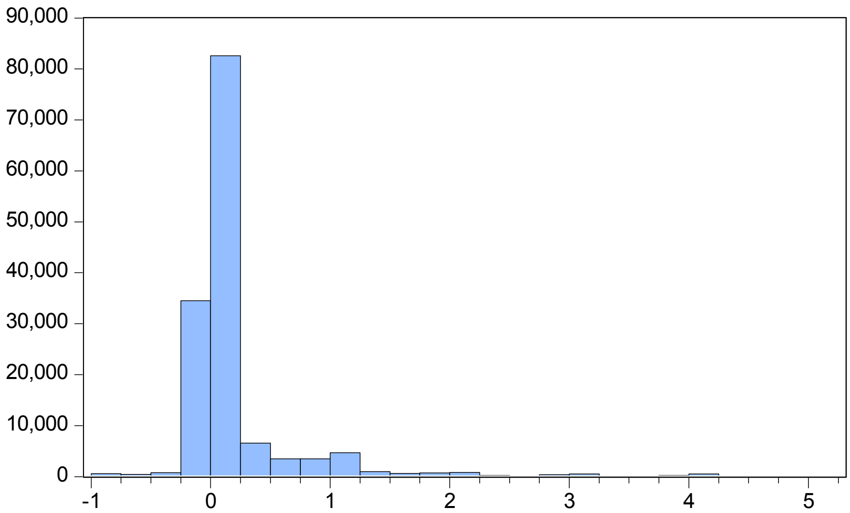
Series: E6
Sample 1990M01 2020M01
Observations 148680

Mean	0.031365
Median	0.000000
Maximum	2.000000
Minimum	-1.000000
Std. Dev.	0.174260
Skewness	5.754301
Kurtosis	47.96644
Jarque-Bera	13346686
Probability	0.000000



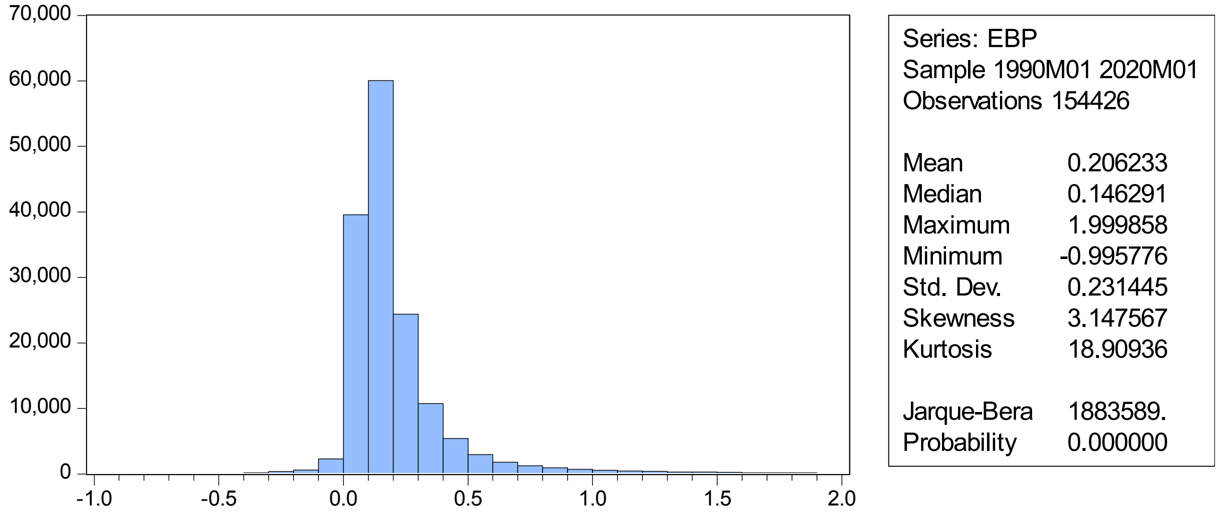
Series: E12
Sample 1990M01 2020M01
Observations 145851

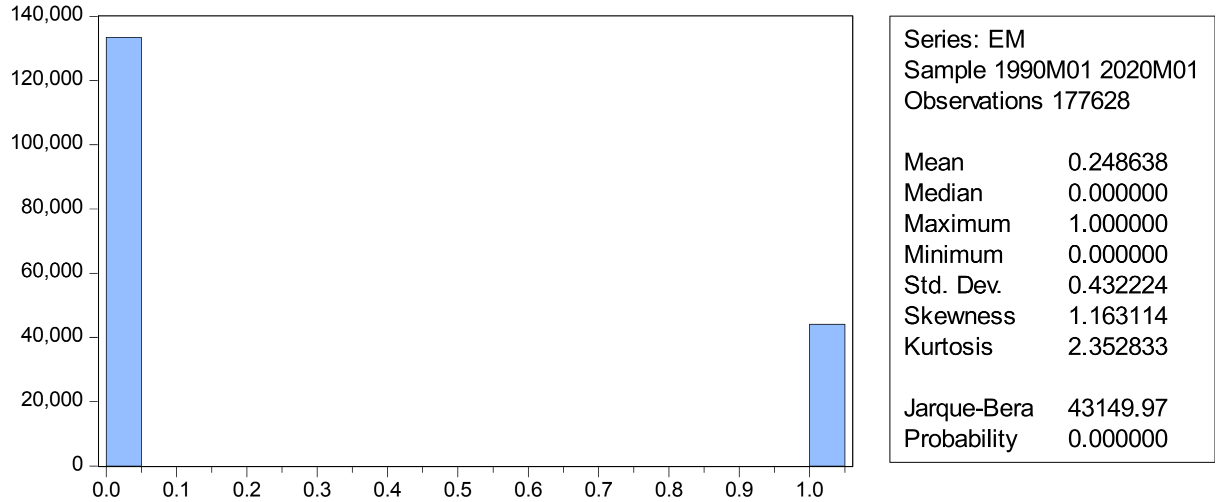
Mean	0.061496
Median	0.000000
Maximum	2.000000
Minimum	-1.000000
Std. Dev.	0.244195
Skewness	3.858878
Kurtosis	23.11393
Jarque-Bera	2820600.
Probability	0.000000

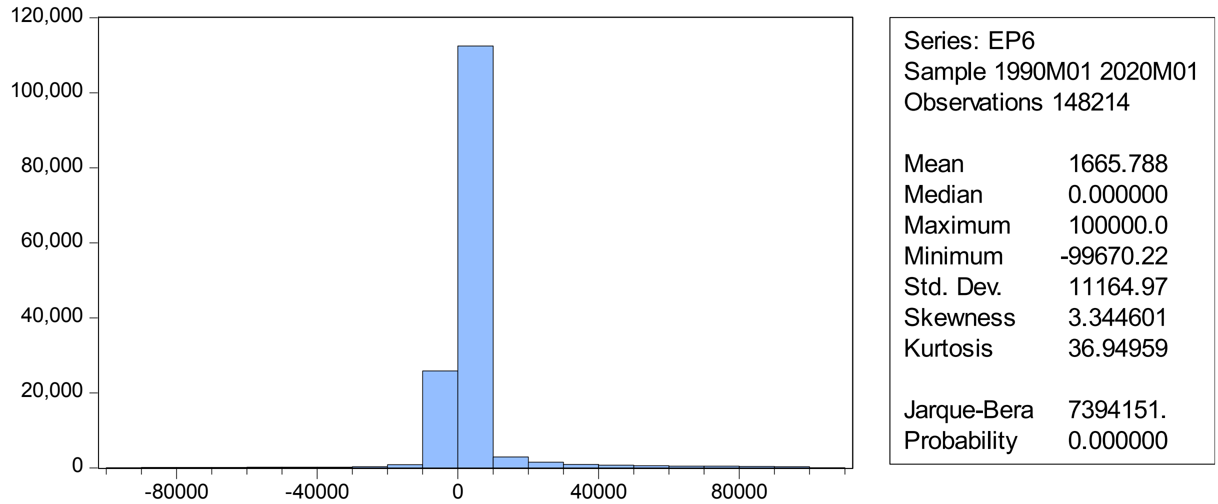


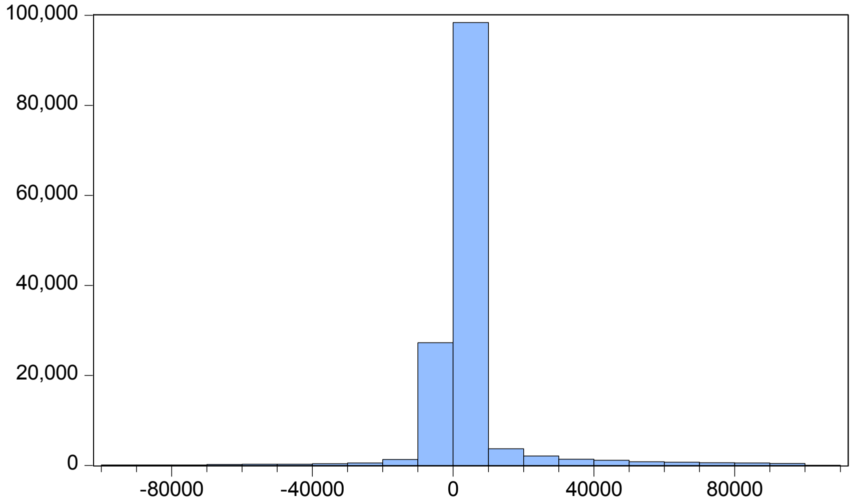
Series: E24
Sample 1990M01 2020M01
Observations 142979

Mean	0.192052
Median	0.002137
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	0.592904
Skewness	4.228592
Kurtosis	24.96135
Jarque-Bera	3299388.
Probability	0.000000


Series: EBP
Sample 1990M01 2020M01
Observations 154426
Mean 0.206233
Median 0.146291
Maximum 1.999858
Minimum -0.995776
Std. Dev. 0.231445
Skewness 3.147567
Kurtosis 18.90936
Jarque-Bera 1883589.
Probability 0.000000

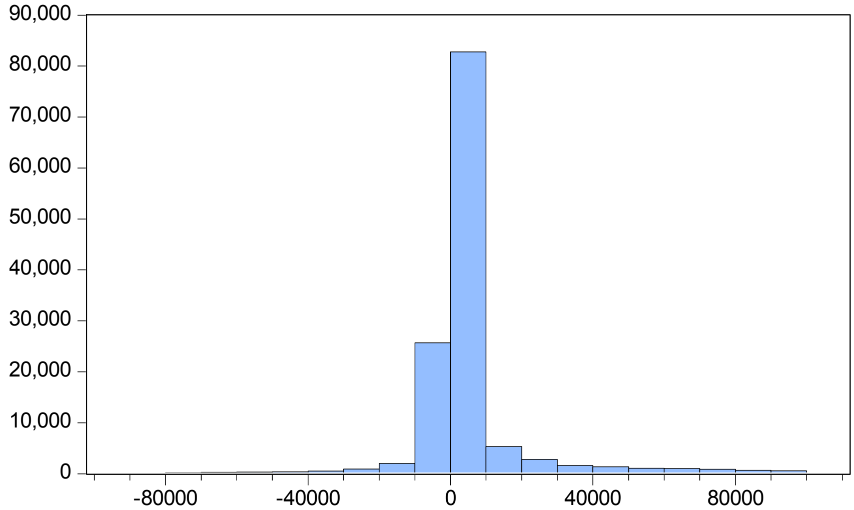

Series: EM
Sample 1990M01 2020M01
Observations 177628
Mean 0.248638
Median 0.000000
Maximum 1.000000
Minimum 0.000000
Std. Dev. 0.432224
Skewness 1.163114
Kurtosis 2.352833
Jarque-Bera 43149.97
Probability 0.000000


Series: EP6
Sample 1990M01 2020M01
Observations 148214
Mean 1665.788
Median 0.000000
Maximum 100000.0
Minimum -99670.22
Std. Dev. 11164.97
Skewness 3.344601
Kurtosis 36.94959
Jarque-Bera 7394151.
Probability 0.000000



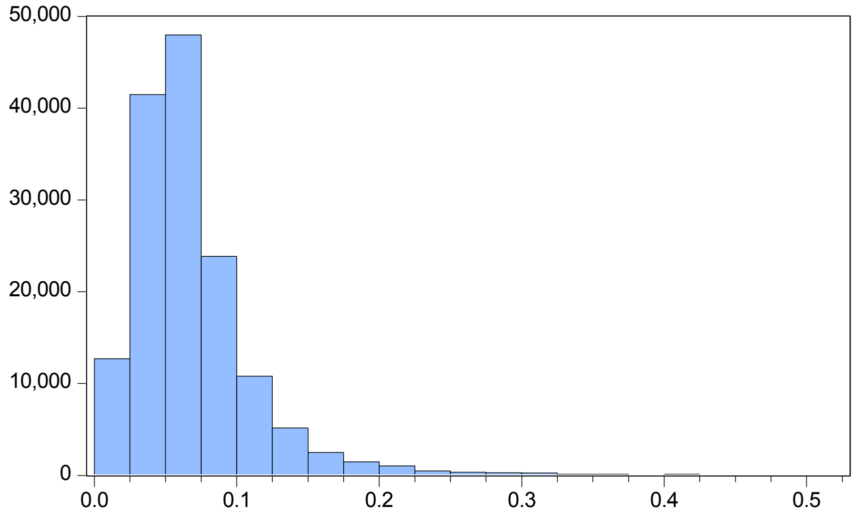
Series: EP12
Sample 1990M01 2020M01
Observations 140155

Mean	2426.185
Median	0.000000
Maximum	100000.0
Minimum	-99389.98
Std. Dev.	13890.66
Skewness	2.478714
Kurtosis	23.21311
Jarque-Bera	2529481.
Probability	0.000000



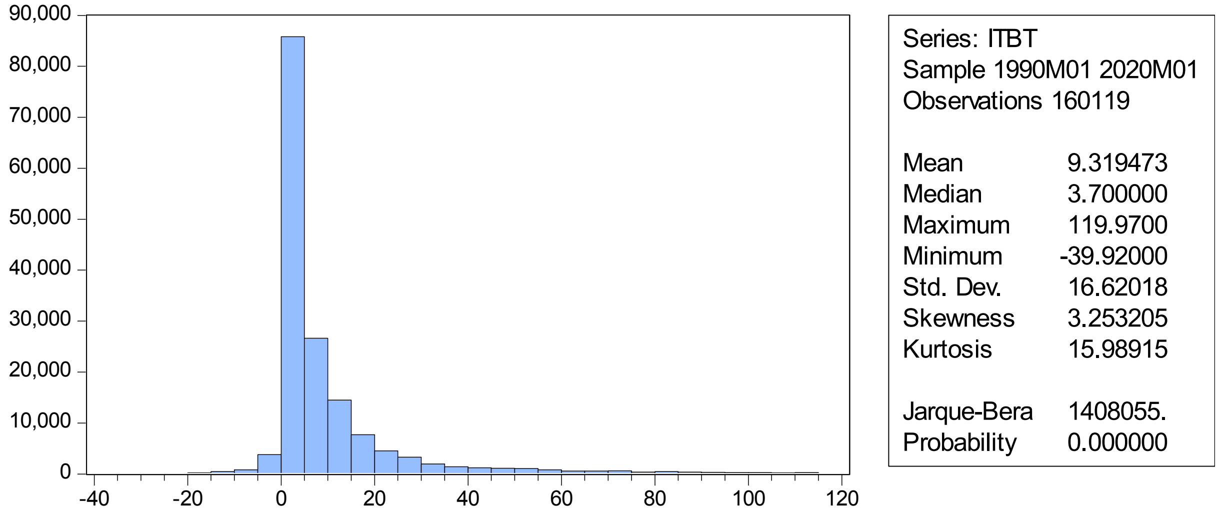
Series: EP24
Sample 1990M01 2020M01
Observations 128844

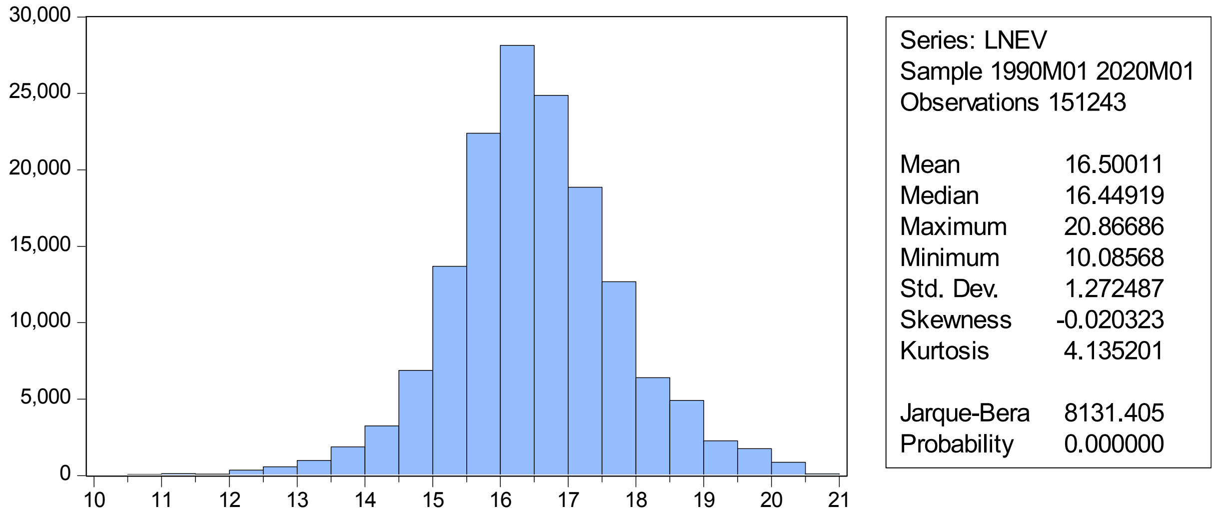
Mean	3396.321
Median	0.000000
Maximum	100000.0
Minimum	-99770.08
Std. Dev.	17241.17
Skewness	1.601800
Kurtosis	15.34635
Jarque-Bera	873430.5
Probability	0.000000

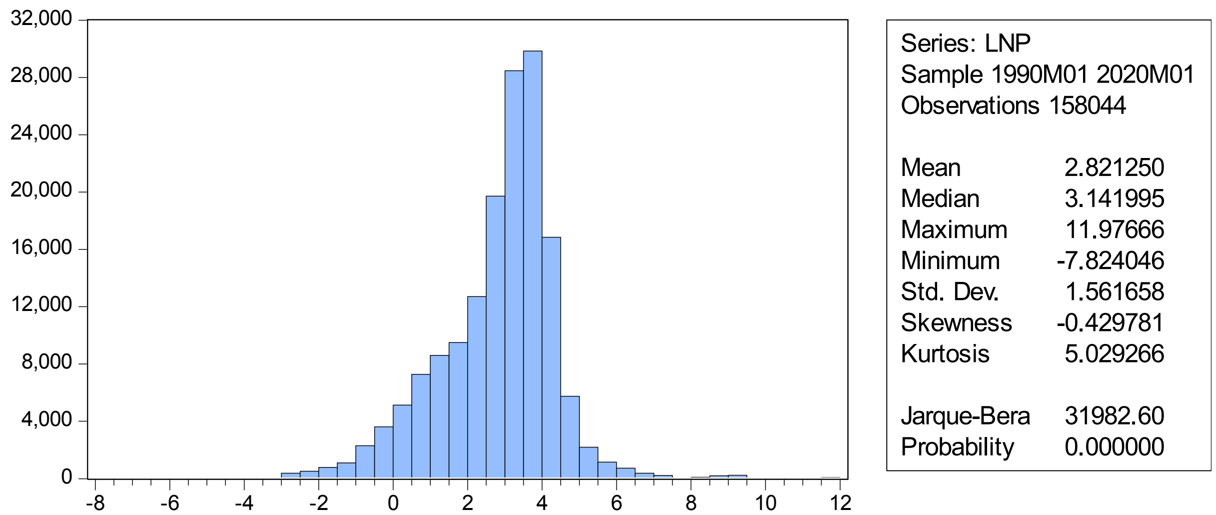


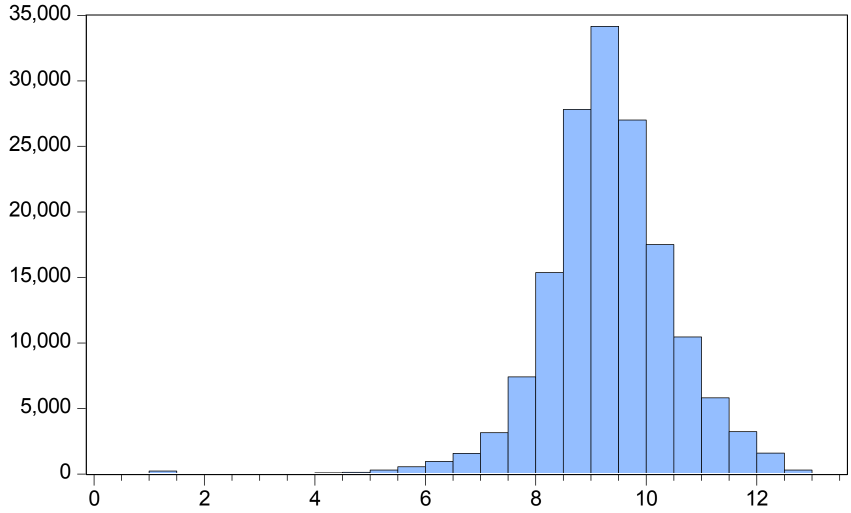
Series: EY
Sample 1990M01 2020M01
Observations 148992

Mean	0.068532
Median	0.059172
Maximum	0.500000
Minimum	2.51e-05
Std. Dev.	0.046051
Skewness	2.862647
Kurtosis	17.72528
Jarque-Bera	1549597.
Probability	0.000000


Series: ITBT
Sample 1990M01 2020M01
Observations 160119
Mean 9.319473
Median 3.700000
Maximum 119.9700
Minimum -39.92000
Std. Dev. 16.62018
Skewness 3.253205
Kurtosis 15.98915
Jarque-Bera 1408055.
Probability 0.000000

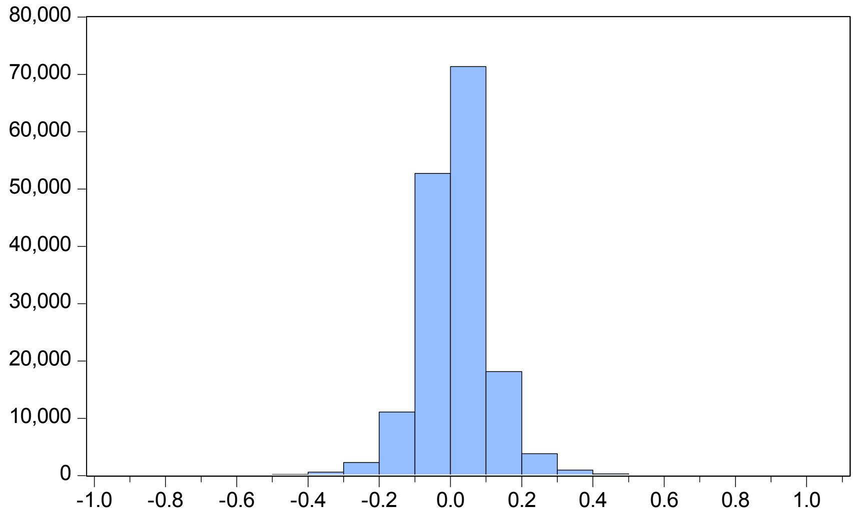

Series: LNEV
Sample 1990M01 2020M01
Observations 151243
Mean 16.50011
Median 16.44919
Maximum 20.86686
Minimum 10.08568
Std. Dev. 1.272487
Skewness -0.020323
Kurtosis 4.135201
Jarque-Bera 8131.405
Probability 0.000000


Series: LNP
Sample 1990M01 2020M01
Observations 158044
Mean 2.821250
Median 3.141995
Maximum 11.97666
Minimum -7.824046
Std. Dev. 1.561658
Skewness -0.429781
Kurtosis 5.029266
Jarque-Bera 31982.60
Probability 0.000000



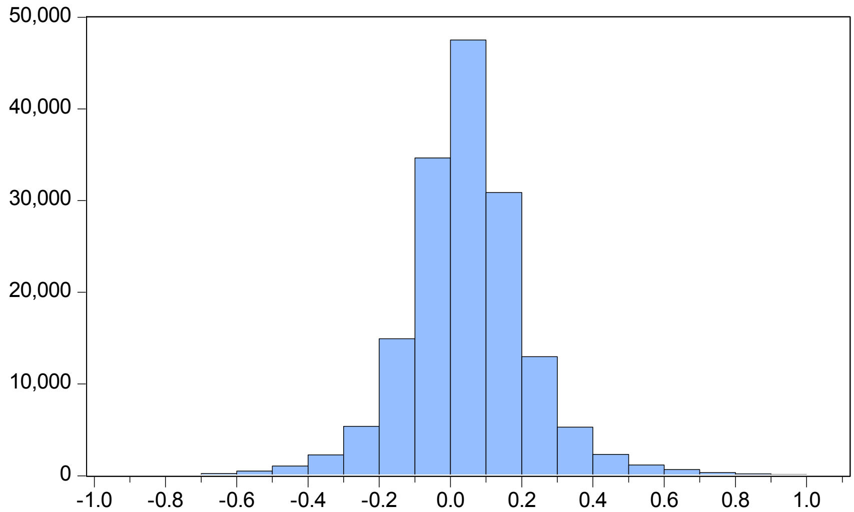
Series: LNMV
Sample 1990M01 2020M01
Observations 157770

Mean	9.325943
Median	9.303554
Maximum	13.44401
Minimum	0.076961
Std. Dev.	1.158016
Skewness	-0.737897
Kurtosis	7.861227
Jarque-Bera	169665.1
Probability	0.000000



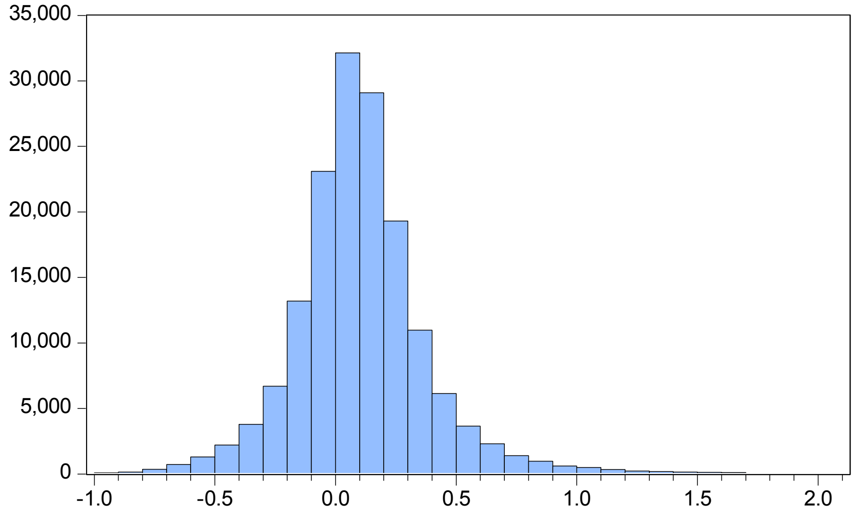
Series: MOM1
Sample 1990M01 2020M01
Observations 161768

Mean	0.015692
Median	0.014031
Maximum	1.000000
Minimum	-1.000000
Std. Dev.	0.100183
Skewness	0.269644
Kurtosis	9.944668
Jarque-Bera	327035.9
Probability	0.000000

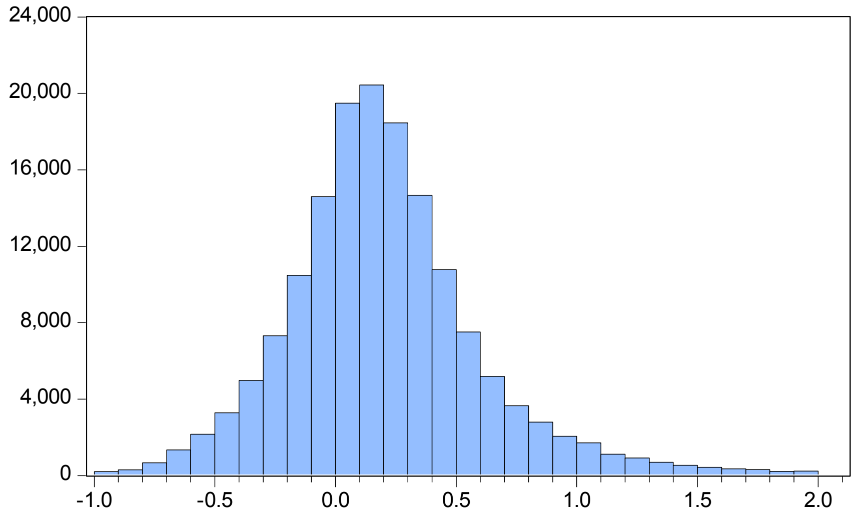


Series: MOM3
Sample 1990M01 2020M01
Observations 160796

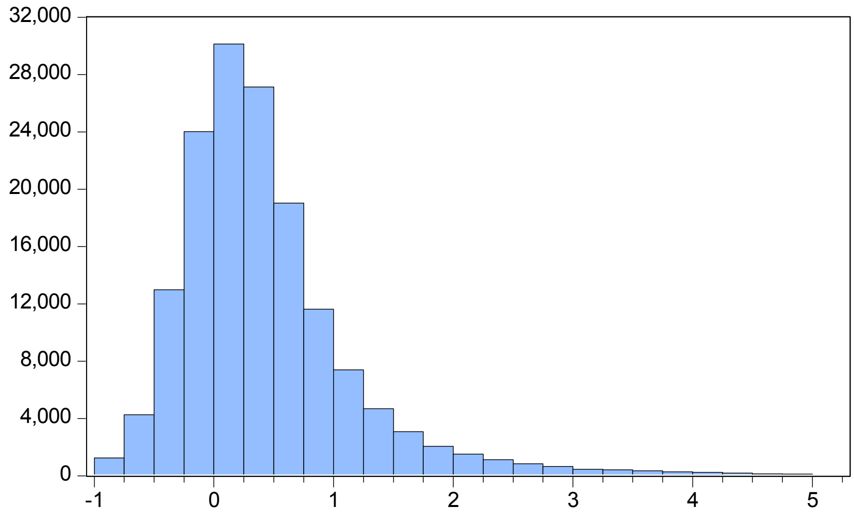
Mean	0.047113
Median	0.042523
Maximum	1.000000
Minimum	-1.000000
Std. Dev.	0.176240
Skewness	0.245360
Kurtosis	6.166612
Jarque-Bera	68795.47
Probability	0.000000



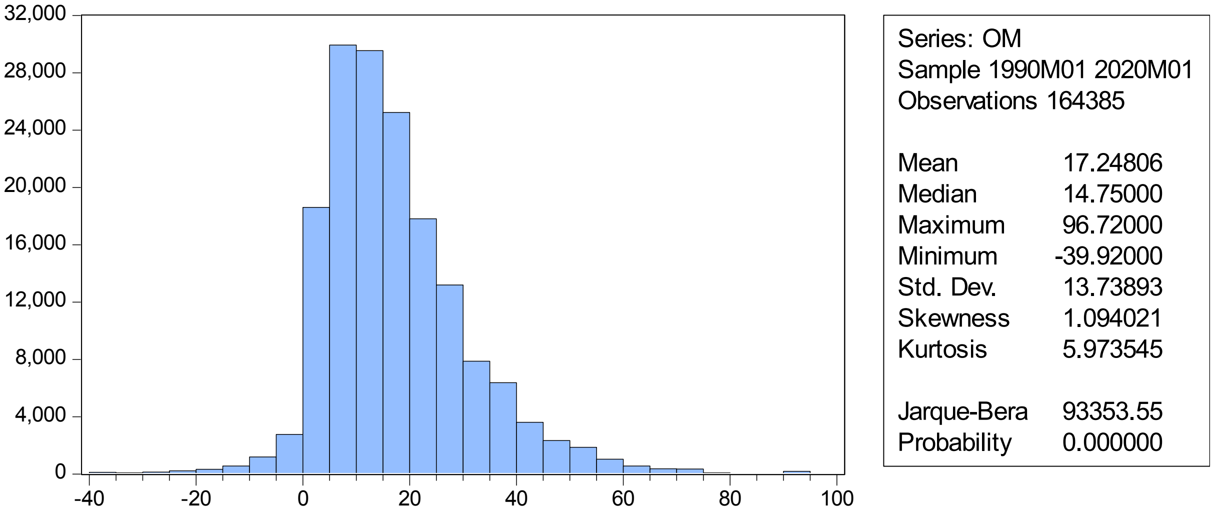
Series: MOM6	
Sample 1990M01 2020M01	
Observations 159964	
Mean	0.105154
Median	0.088154
Maximum	2.000000
Minimum	-1.000000
Std. Dev.	0.281125
Skewness	0.929165
Kurtosis	7.529819
Jarque-Bera	159781.7
Probability	0.000000



Series: MOM12	
Sample 1990M01 2020M01	
Observations 156894	
Mean	0.200215
Median	0.166568
Maximum	2.000000
Minimum	-1.000000
Std. Dev.	0.402688
Skewness	0.772084
Kurtosis	4.899915
Jarque-Bera	39185.13
Probability	0.000000



Series: MOM24	
Sample 1990M01 2020M01	
Observations 153837	
Mean	0.428173
Median	0.287282
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	0.744711
Skewness	1.883698
Kurtosis	8.803559
Jarque-Bera	306870.0
Probability	0.000000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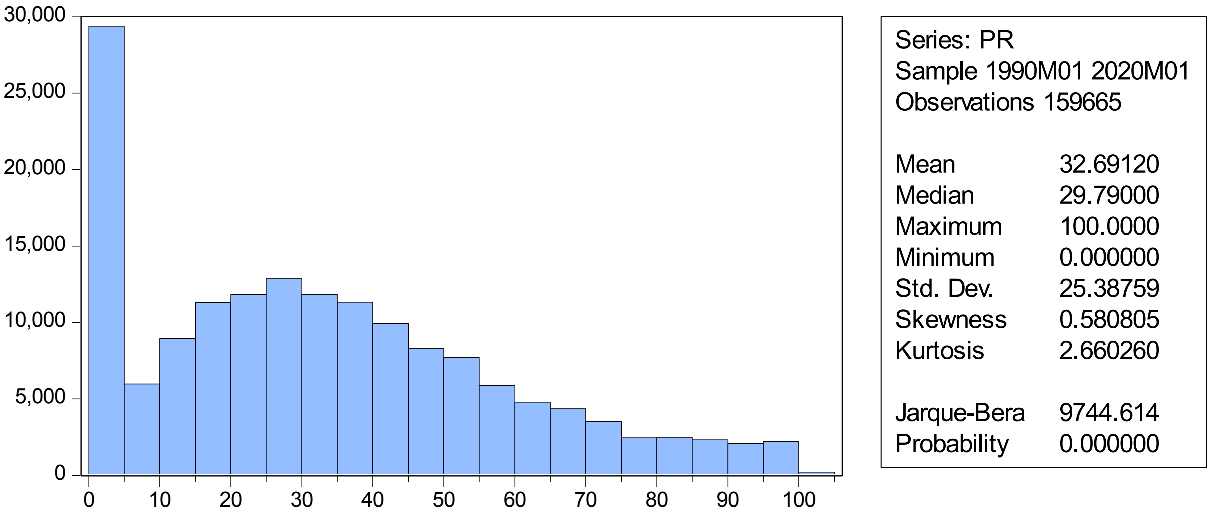
Series: OM
Sample 1990M01 2020M01
Observations 164385
Mean 17.24806
Median 14.75000
Maximum 96.72000
Minimum -39.92000
Std. Dev. 13.73893
Skewness 1.094021
Kurtosis 5.973545
Jarque-Bera 93353.55
Probability 0.000000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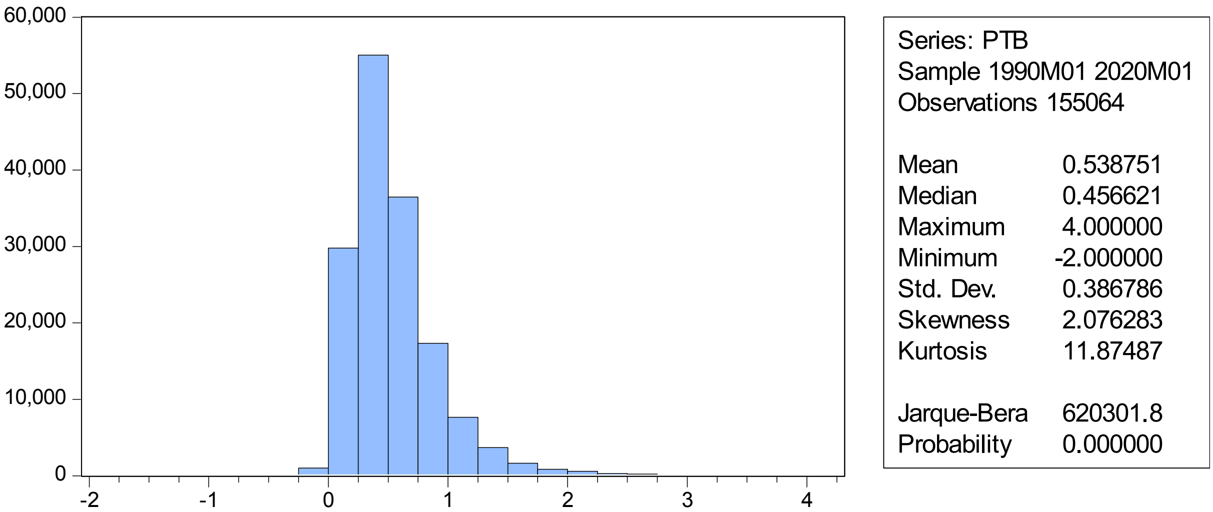
Series: PR
Sample 1990M01 2020M01
Observations 159665
Mean 32.69120
Median 29.79000
Maximum 100.0000
Minimum 0.000000
Std. Dev. 25.38759
Skewness 0.580805
Kurtosis 2.660260
Jarque-Bera 9744.614
Probability 0.000000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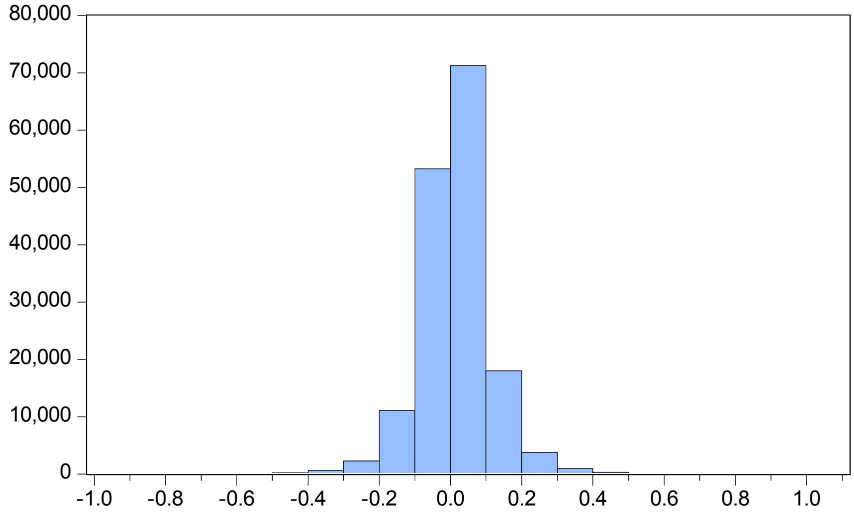
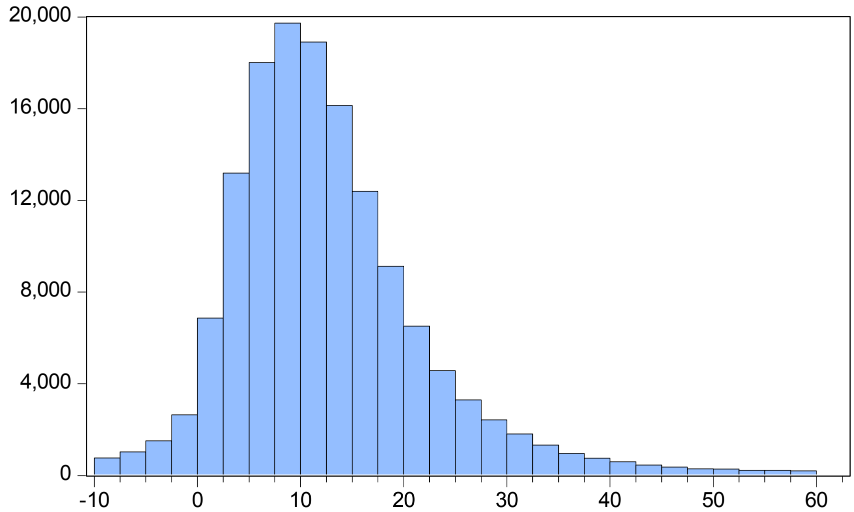
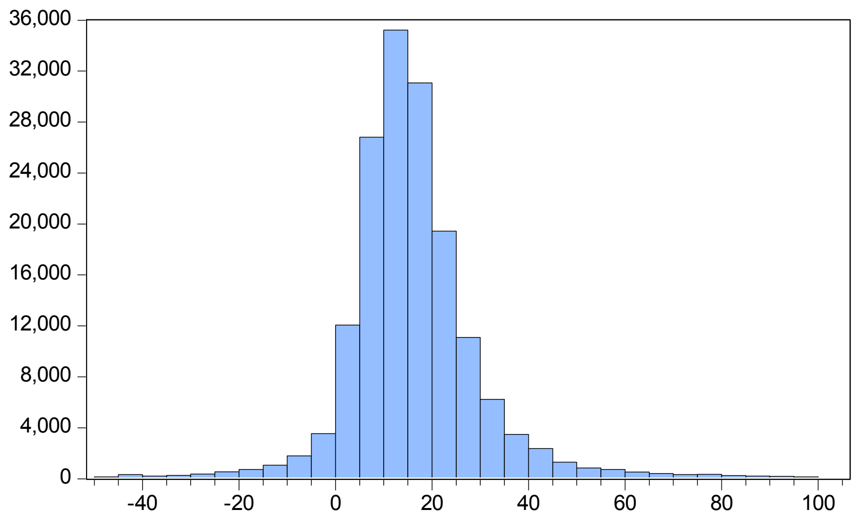
Series: PTB
Sample 1990M01 2020M01
Observations 155064
Mean 0.538751
Median 0.456621
Maximum 4.000000
Minimum -2.000000
Std. Dev. 0.386786
Skewness 2.076283
Kurtosis 11.87487
Jarque-Bera 620301.8
Probability 0.000000



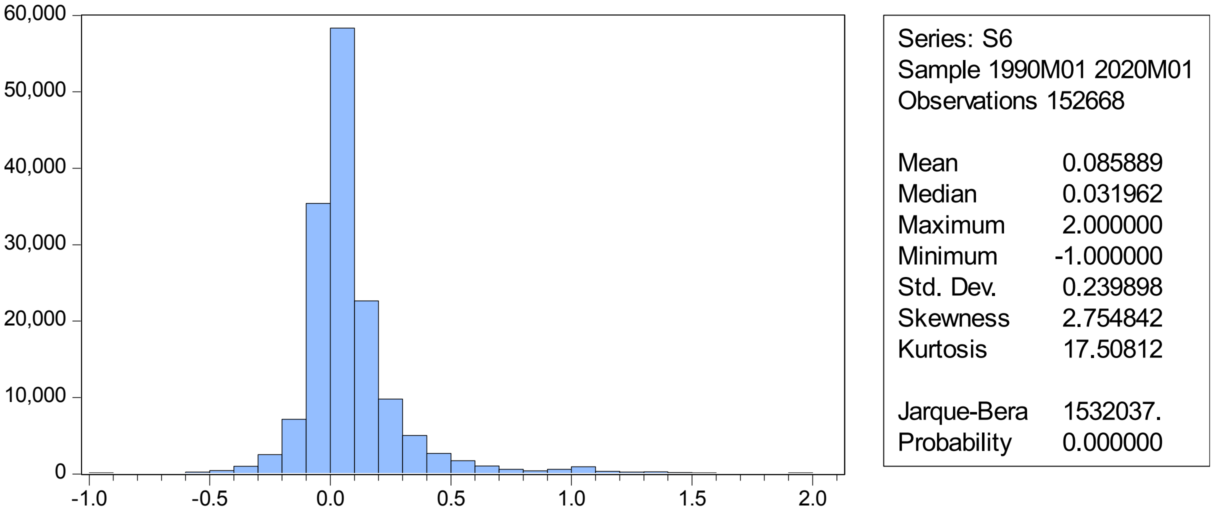
Series: RET	
Sample 1990M01 2020M01	
Observations 162061	
Mean	0.015256
Median	0.013505
Maximum	1.000000
Minimum	-1.000000
Std. Dev.	0.100016
Skewness	0.278122
Kurtosis	10.00018
Jarque-Bera	332980.6
Probability	0.000000

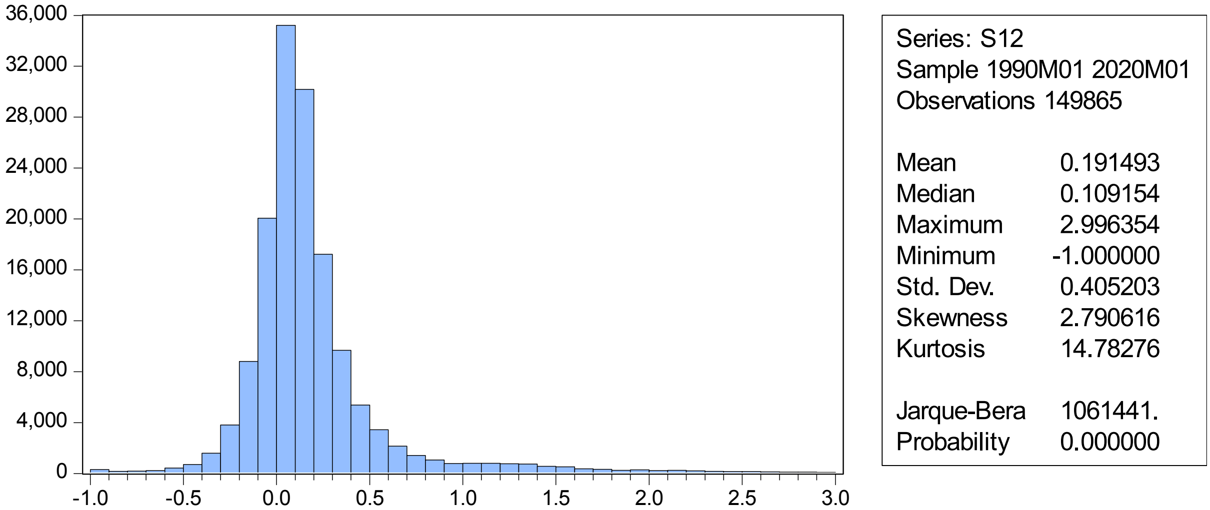


Series: ROA	
Sample 1990M01 2020M01	
Observations 144666	
Mean	12.61058
Median	11.10779
Maximum	60.00000
Minimum	-9.999155
Std. Dev.	9.501044
Skewness	1.256256
Kurtosis	6.004021
Jarque-Bera	92446.77
Probability	0.000000



Series: ROE	
Sample 1990M01 2020M01	
Observations 162015	
Mean	16.10321
Median	14.69000
Maximum	100.0000
Minimum	-50.00000
Std. Dev.	14.12678
Skewness	0.949278
Kurtosis	9.127983
Jarque-Bera	277833.3
Probability	0.000000


Series: S6
Sample 1990M01 2020M01
Observations 152668
Mean 0.085889
Median 0.031962
Maximum 2.000000
Minimum -1.000000
Std. Dev. 0.239898
Skewness 2.754842
Kurtosis 17.50812
Jarque-Bera 1532037.
Probability 0.000000


Series: S12
Sample 1990M01 2020M01
Observations 149865
Mean 0.191493
Median 0.109154
Maximum 2.996354
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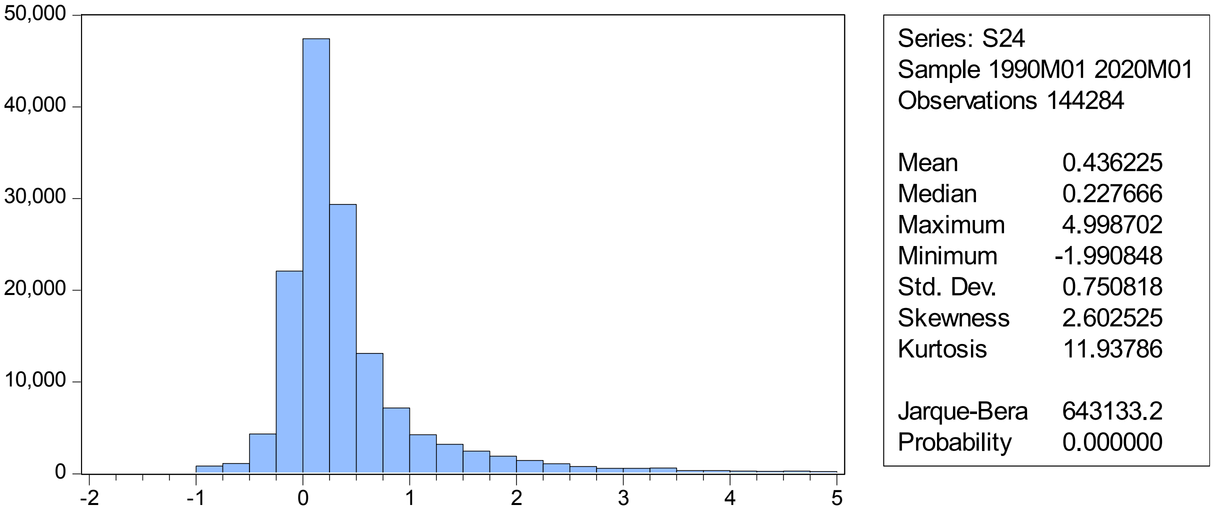
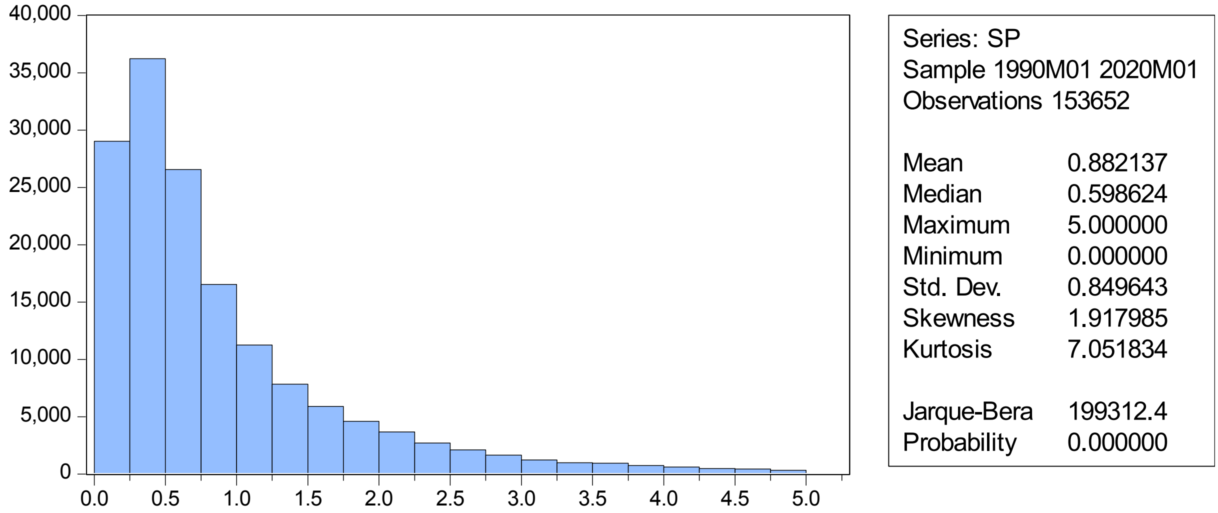
Std. Dev. 0.405203
Skewness 2.790616
Kurtosis 14.78276
Jarque-Bera 1061441.
Probability 0.000000


Series: S24
Sample 1990M01 2020M01
Observations 144284
Mean 0.436225
Median 0.227666
Maximum 4.998702
Minimum -1.990848
Std. Dev. 0.750818
Skewness 2.602525
Kurtosis 11.93786
Jarque-Bera 643133.2
Probability 0.000000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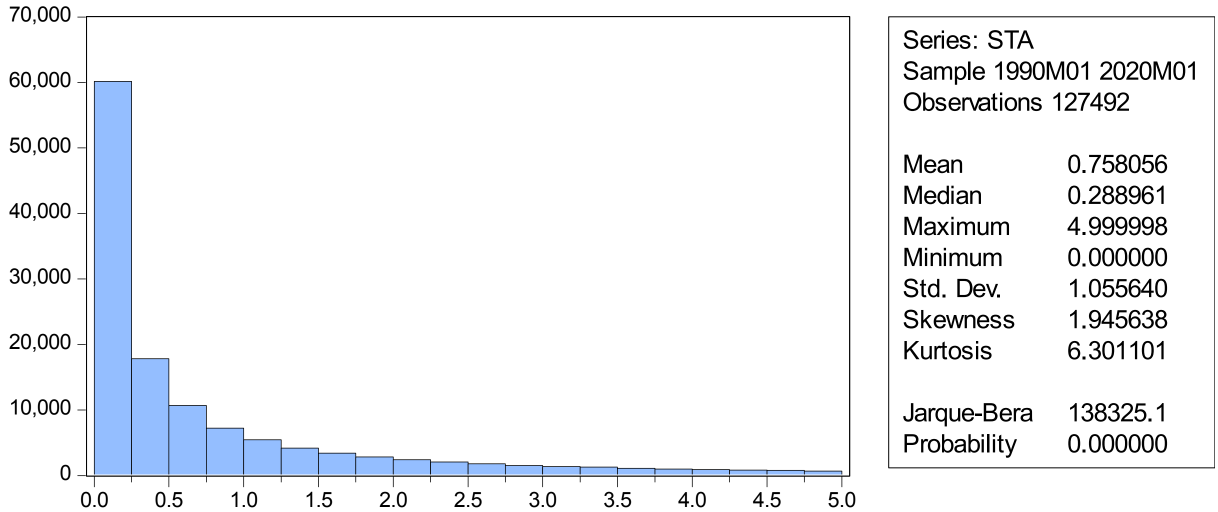
Series: SP
Sample 1990M01 2020M01
Observations 153652
Mean 0.882137
Median 0.598624
Maximum 5.000000
Minimum 0.000000
Std. Dev. 0.849643
Skewness 1.917985
Kurtosis 7.051834
Jarque-Bera 199312.4
Probability 0.000000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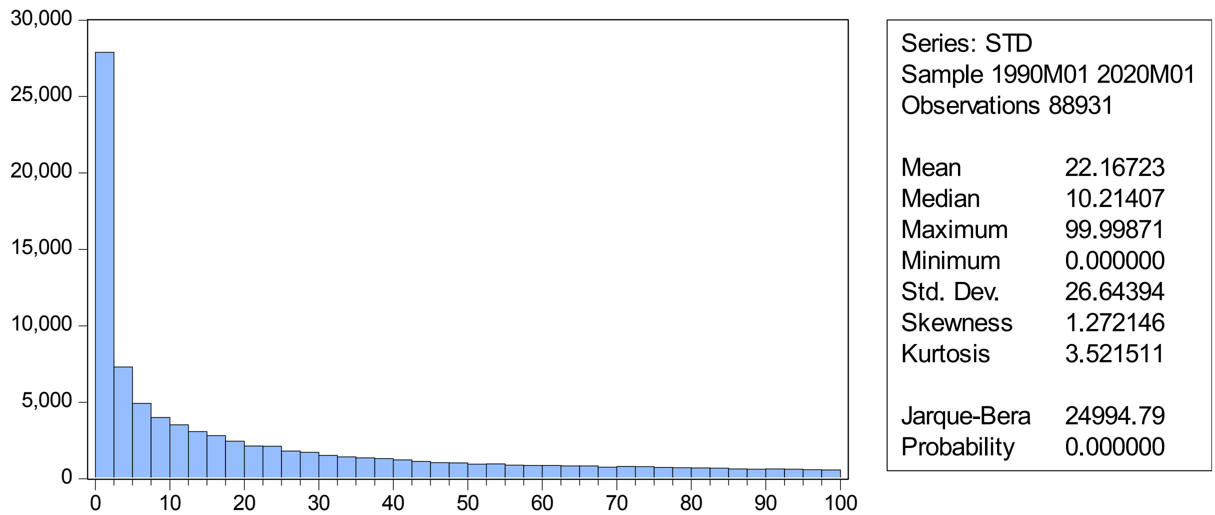
Series: STA
Sample 1990M01 2020M01
Observations 127492
Mean 0.758056
Median 0.288961
Maximum 4.999998
Minimum 0.000000
Std. Dev. 1.055640
Skewness 1.945638
Kurtosis 6.301101
Jarque-Bera 138325.1
Probability 0.000000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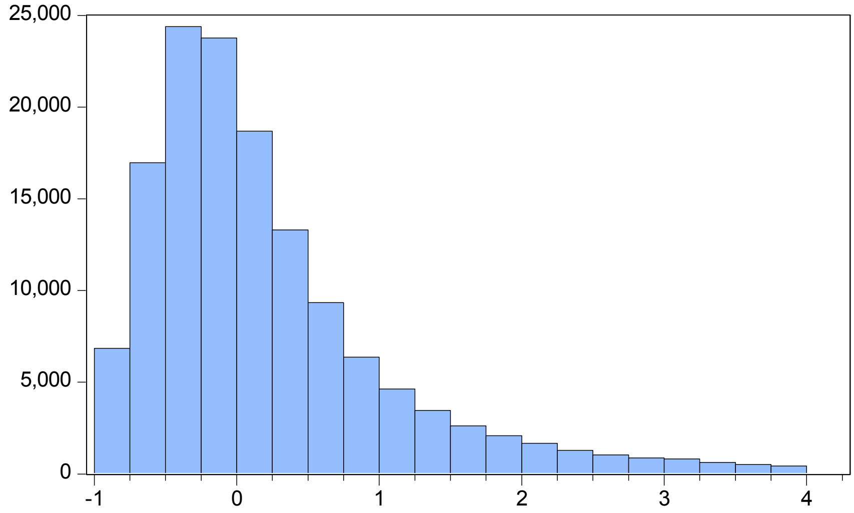
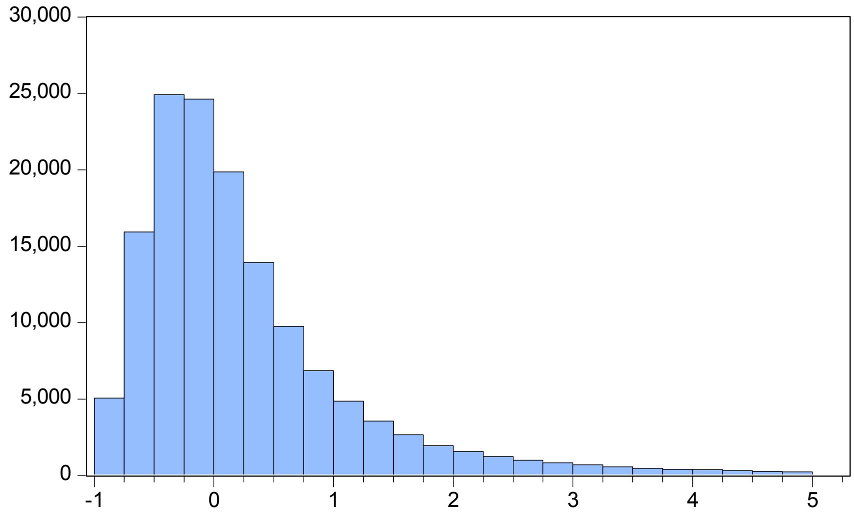
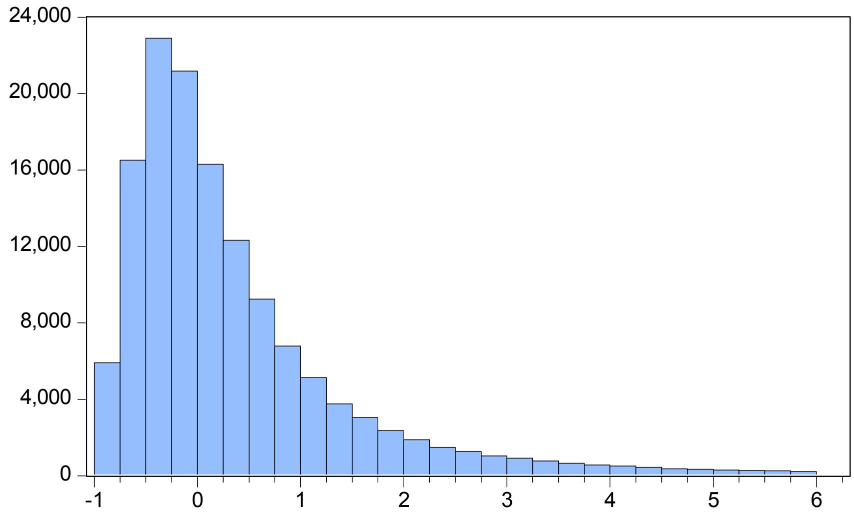
Series: STD
Sample 1990M01 2020M01
Observations 88931
Mean 22.16723
Median 10.21407
Maximum 99.99871
Minimum 0.000000
Std. Dev. 26.64394
Skewness 1.272146
Kurtosis 3.521511
Jarque-Bera 24994.79
Probability 0.000000



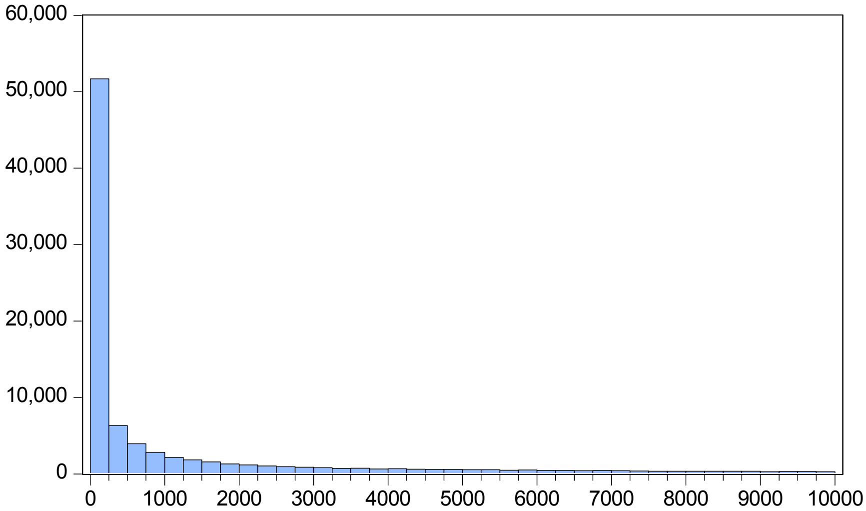
Series: TVO6	
Sample 1990M01 2020M01	
Observations 139782	
Mean	0.201104
Median	-0.025472
Maximum	4.000000
Minimum	-1.000000
Std. Dev.	0.864632
Skewness	1.612280
Kurtosis	5.958513
Jarque-Bera	111537.8
Probability	0.000000



Series: TVO12	
Sample 1990M01 2020M01	
Observations 142035	
Mean	0.249578
Median	0.003742
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	0.921037
Skewness	1.939536
Kurtosis	7.799609
Jarque-Bera	225382.6
Probability	0.000000



Series: TVO24	
Sample 1990M01 2020M01	
Observations 136791	
Mean	0.357713
Median	0.023936
Maximum	6.000000
Minimum	-1.000000
Std. Dev.	1.118192
Skewness	2.007228
Kurtosis	7.841723
Jarque-Bera	225466.6
Probability	0.000000



Series: VOL	
Sample 1990M01 2020M01	
Observations 88931	
Mean	1201.278
Median	104.3273
Maximum	9999.741
Minimum	0.000000
Std. Dev.	2190.799
Skewness	2.196722
Kurtosis	7.065865
Jarque-Bera	132780.0
Probability	0.000000

Appendix G: E-Views Standardised Slopes Program

The program below was coded for E-Views in order to test the panel of returns and firm-specific data for the 1468 shares over the 121-month period. The data was standardised, trimmed to within 3 standard deviations of the mean, and regressed against forward returns. The resulting payoffs for each month are the core of the Fama-MacBeth analysis.

```
!minmonth=164
!maxmonth=284
!totalshares=2000
!totalmonths=361

' 1990.01 to 2003.08 = 120+12+12+12+8 = 164
' 2003.08 to 2013.08 = 120
' 2013.08 to 2020.01 = 77
' 1990.01 to 2020.01 = 361

Table Slopes
!row=1
Smpl @all

for !month = !minmonth to !maxmonth

' LOOP (1) through months

   Smpl 1990.01 + !month-1  1990.01 + !month-1

   !row=!row+1
   Slopes(!row,1)=!month
   !column=1


   For %0 PTB CFP DY EY SP EBP S6 S12 S24 E6 E12 E24 D6 D12 D24 DP12 EP6 EP12 EP24
   PR ROE ROA STA DC OM CXS MOM1 MOM3 MOM6 MOM12 MOM24 LNP LNMV LNEV
   TVO6 TVO12 TVO24 STD VOL BET ITBT DE DA EM

   ' LOOP (2) through style factors

      !column=!column+1
      Slopes(1,!column)=%0

      genr t{%0} = {%0}
      ' Generating variable t
      !counter=0
      !zero=0


      For !share=1 to !totalshares

         !pos=(!month+(!share-1)*361)

         If t{%0}(!pos)<>NA then
            !counter = !counter+1
         Endif
```

```
        If t{%0}(!pos) > 0 then
            !zero = !zero+1
        Endif

        If t{%0}(!pos) < 0 then
            !zero = !zero + 1
        Endif

    next

    If @stdev({%0}) = 0 then
        Genr s{%0} = 0
    Else
        Genr s{%0} = ({%0} - @mean({%0}))/@stdev({%0})
    Endif

    For !share = 1 to !totalshares
        !pos = (!month+(!share-1)*361)

        !test = s{%0}(!pos)

        If !test > 3 then
            s{%0}(!pos)=3
        endif

        if !test < -3 then
            s{%0}(!pos)=-3
        endif

    next

    series z{%0}

    if !counter > 1 then
    if !zero > 1 then
    equation stuff.ls RET c s{%0}
    slopes(!row,!column) = c(2)
    endif
    endif

  next

next
```

Appendix H: DataStream Datatype Definitions

Each of the DataStream dadatypes used in this analysis is presented below with the official DataStream definition of each. These datatypes were either used on their own, or in a calculation of required ratios and growth measures.

Datatype Mnemonic	Datatype Name	Datatype Definition
MV X(MV)~U$	Market Value (Capitalisation)	"Market value on Datastream is the share price multiplied by the number of ordinary shares in issue. The amount in issue is updated whenever new tranches of stock are issued or after a capital change. • For companies with more than one class of equity capital, the market value is expressed according to the individual issue. • Market value is displayed in millions of units of local currency. "
RI X(RI)~U$	Total Returns Index	"A return index (RI) is available for individual equities and unit trusts. This shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date. Method: the discrete quantity of dividend paid is added to the price on the ex-date of the payment. Then: $RI_t = RI_{t-1} * \frac{P_t}{P_{t-1}}$ except when t = ex-date of the dividend payment D_t then: $RI_t = RI_{t-1} * \frac{P_t + D_t}{P_{t-1}}$ Where: P_t = price on ex-date P_{t-1} = price on previous day D_t = dividend payment associated with ex-date t Gross dividends are used where available and the calculation ignores tax and re-investment charges. Adjusted closing prices are used throughout to determine price index and hence return index."
INDM	Industrial Grouping	"This datatype returns the Datastream level 6 industrial classification name, for example, 'Breweries'."
MNEM	Mnemonic	"This is a unique identification code, assigned by Datastream. It can be used to access data for a particular issue on all Research programs (that is, it is interchangeable with the Datastream code number). It consists of up to 6 characters, for example, RLRC for Rolls-Royce. "
		"This is the total number of ordinary shares that

NOSH	Number of shares in issue	represent the capital of the company. The datatype is expressed in thousands. For shares with more than one class of equity issue, (NOSH) is held separately for each issue. The amount is updated whenever new tranches of stock are issued or after capital changes. "
BETA	Beta	"The beta is calculated as the relationship between the volatility of the stock and the volatility of the market. This coefficient is based on between 23 and 35 consecutive month end price percent changes and their relativity to a local market index. Beta factors are available for Datastream sector indices compared to the market index. The method of calculation is identical to that for individual equities except that price indices are used instead of stock prices."
DWCX X(DWCX)~U$	CAPEX (Capital Expenditure)	"The Datastream Worldscope (DW) datatypes are a set of Datastream Global Equity index and security valuation datatypes using Worldscope data. The data is based on a trailing twelve month period if applicable and represents the sum of the relevant item reported in the last twelve months. From the fiscal period 2002, the items are populated from the quarterly, semi-annual and trimester time series based on the availability of the underlying data. When trailing twelve month data is unavailable or for values before fiscal period 2002, the annual Worldscope datatype is used as indicated below. Capital Expenditures represent the funds used to acquire fixed assets other than those associated with acquisitions. It includes but is not restricted to: Additions to property, plant and equipment Investments in machinery and equipment."
PC	Price / Cash Earnings Ratio	"This is the share price divided by the cash earnings per share for the appropriate financial period. Cash earnings per share/cash flow per share – datatype (CASH). This is defined as the cash flow items "Funds from operations" (Worldscope item 05501 for non-US companies and item 05502 for US companies) per share. Free Cash Flow = Net Cash Flow – Operating Activities represent the net cash receipts and disbursements resulting from the operations of the company. It is the sum of Funds from Operations, Funds From/Used for Other Operating Activities and Extraordinary Items.

		Fully diluted earnings per share represents the net income per share assuming the conversion of all convertible securities including convertible preferred stock and convertible debentures and the exercise of all outstanding stock options and warrants. It represents earnings for the 12 months ended the last calendar quarter for U.S. companies and the fiscal year for non-U.S. companies."
DCV	Dividend Cover	"The dividend cover is the maximum dividend that a company could pay out of earnings dividend by the actual dividend paid. For all markets except the UK, the value is calculated as: $\frac{earnings(current)}{dividend(current)}$ For UK, the estimated full earnings figure (earnings if all the profit is distributed as dividend) is divided by the gross dividend amount, including any tax credit."
DY	Dividend Yield	• "The dividend yield expresses the dividend per share as a percentage of the share price. The underlying dividend is calculated according to the same principles as datatypeDPSC (Dividend per share, current rate) in that it is based on an anticipated annual dividend and excludes special or once-off dividends. • Dividend yield is calculated on gross dividends (including tax credits) where available. Note that dividend yield for UK, Irish and French stocks is calculated on gross dividends (including tax credits), although dividends per share for these countries are displayed net."
PE	Price / Earnings Ratio	"This is the price divided by the earnings rate per share at the required date. For full details of the price and earnings figures used in any particular case, see the Price and Earnings per share topics. EARNINGS BEFORE INTEREST AND TAXES (EBIT) represent the earnings of a company before interest expense and income taxes. It is calculated by taking the pretax income and adding back interest expense on debt and subtracting interest capitalized."
DWED X(DWED)~U$	EBITDA (Earnings before Interest Taxation Depreciation and	"The Datastream Worldscope (DW) datatypes are a set of Datastream Global Equity index and security valuation datatypes using Worldscope data. The data is based on a trailing twelve month period if applicable and represents the sum of the relevant item reported in the last twelve months. From the fiscal period 2002, the items are

	Ammortisation)	populated from the quarterly, semi-annual and trimester time series based on the availability of the underlying data. When trailing twelve month data is unavailable or for values before fiscal period 2002, the annual Worldscope datatype is used as indicated below. Earnings before Interest, Taxes and Depreciation (EBITDA) represent the earnings of a company before interest expense, income taxes and depreciation. It is calculated by taking the pre- tax income and adding back interest expense on debt and depreciation, depletion and amortization and subtracting interest capitalized.”
IDTDDEPS	Earnings per Share	“The latest annualised rate that may reflect the last financial year or be derived from an aggregation of interim period earnings. Data is either provided by local sources or Worldscope. “
ICBT	Interest Cover	“This is defined as Earnings Before Interest and Tax / (Interest Expense on Debt less Interest Capitalised) and is calculated using the following Worldscope data items: WC18191 / (WC01251-WC01255).”
GGISO	ISO Country Code	“The datatype returns the 2 character ISO country code for a stock, as defined by the datatype for the geographical classification of company (GEOGC). “
POUT	Payout Ratio	“This is the ratio of dividends per share divided by the net earnings per share (adjusted) for the last financial period. It is available on program 101S, and is calculated from Datastream’s company accounts items 190 and 211 as follows: $POUT = \frac{190}{211}$ Where: 190 = Ratio of dividends per share 211 = Net earnings per share – adjusted”
P X(P)~U$	Price (Adjusted – Default)	“Datatype (P) represents the official closing price. This is the default datatype for all equities. The ‘current’ price on Datastream’s equity programs is the latest price available to us from the appropriate market in primary units of currency (except in the case of the UK where price is given in pence). It is the previous day’s closing price from the default exchange except where more recent or real-time prices are available, as listed in the Data sources & updating

		procedures section of this help system. The 'current' prices taken at the close of market are stored each day. These stored prices are adjusted for subsequent capital actions, and this adjusted figure then becomes the default price offered on all Research programs. The actual historical prices can be accessed using the unadjusted price datatype (UP). Prices are generally based on 'last trade' or an official price fixing. For stocks which are listed on more than one exchange within a country, default prices are taken from the primary exchange of that country (note that this is not necessarily the 'home' exchange of the stock). For Japan and Germany , prices from the secondary markets can be obtained by qualifying the price datatype with an exchange code (see below for details). "
PTBV	Price to book value	"This is the share price divided by the book value per share."
X(WC08101)~U$	Quick Ratio	"A liquidity ratio calculated annually based on the equation: Cash & Equivalents + Receivables (Net)) / Current Liabilities-Total"
DWRE	Return on Equity (ROE)	"The DatastreamWorldscope (DW) datatypes are a set of Datastream Global Equity index and security valuation datatypes using Worldscope data. The data is based on a trailing twelve month period if applicable and represents the sum of the relevant item reported in the last twelve months. From the fiscal period 2002, the items are populated from the quarterly, semi-annual and trimester time series based on the availability of the underlying data. When trailing twelve month data is unavailable or for values before fiscal period 2002, the annual Worldscopedatatype is used as indicated below. DWNP / DWSE x 100 % DWNP = Net Profit DWSE = Common/Shareholders Equity DWRE = N/A when DWSE is negative"
VO	Turnover by Volume	"This shows the number of shares traded for a stock. The figure is always expressed in thousands. Both daily and non-daily figures are adjusted for capital events. However, if a capital event occurs in the latest period of a non-daily request, then the volume for that particular period only is retrieved as unadjusted. For stocks, which are traded on more than one exchange within a country, default volumes

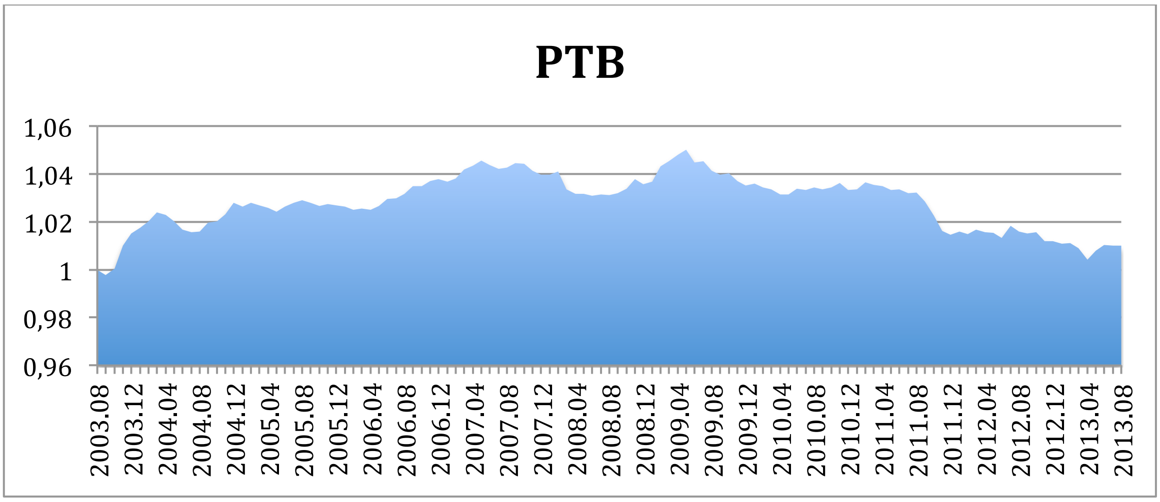
		are taken from the primary exchange of that country (note that this is not necessarily the 'home' exchange of the stock). "
DWTA X(DWTA)~U$	Total Assets	"The DatastreamWorldscope (DW) datatypes are a set of Datastream Global Equity index and security valuation datatypes using Worldscope data. The data is based on a trailing twelve month period if applicable and represents the sum of the relevant item reported in the last twelve months. From the fiscal period 2002, the items are populated from the quarterly, semi-annual and trimester time series based on the availability of the underlying data. When trailing twelve month data is unavailable or for values before fiscal period 2002, the annual Worldscopedatatype is used as indicated below. All Industries: Total Assets represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. Banks: Total Assets represent the sum of cash & due from banks, total investments, net loans, customer liability on acceptances (if included in total assets), investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment and other assets. Insurance Companies: Total Assets represent the sum of cash, total investments, premium balance receivables, investments in unconsolidated subsidiaries, net property, plant and equipment and other assets. Other Financial Companies: Total Assets represent the sum of cash & equivalents, receivables, securities inventory, custody securities, total investments, net loans, net property, plant and equipment, investments in unconsolidated subsidiaries and other assets."
X(1301)~U$	Total Debt	Accounting Line Item - no definition available
X(1504)~U$	Enterprise Value	"All Industries: Market Capitalization at fiscal year end date + Preferred Stock + Minority Interest + Total Debt minus Cash. Cash represents Cash & Due from Banks for Banks, Cash for Insurance Companies and Cash & Short Term Investments for all other industries."
X(1505)~U$	Sales per Share	Accounting Line Item - no definition available
X(190)~U$	Dividends per Share	Accounting Line Item - no definition available
X(713)~U$	Operating profit margin	Accounting Line Item - no definition available

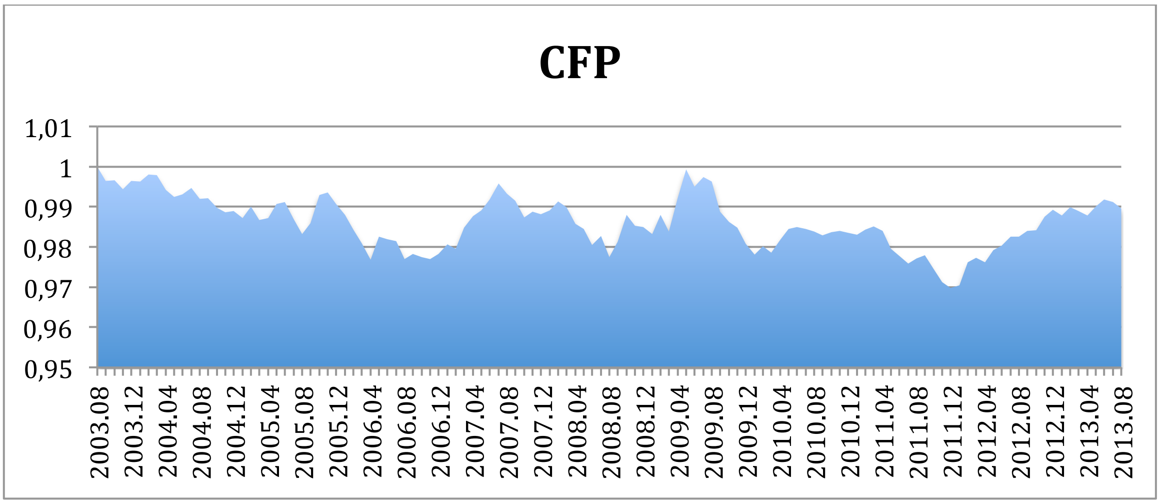
Appendix I: Fama-MacBeth Method Results

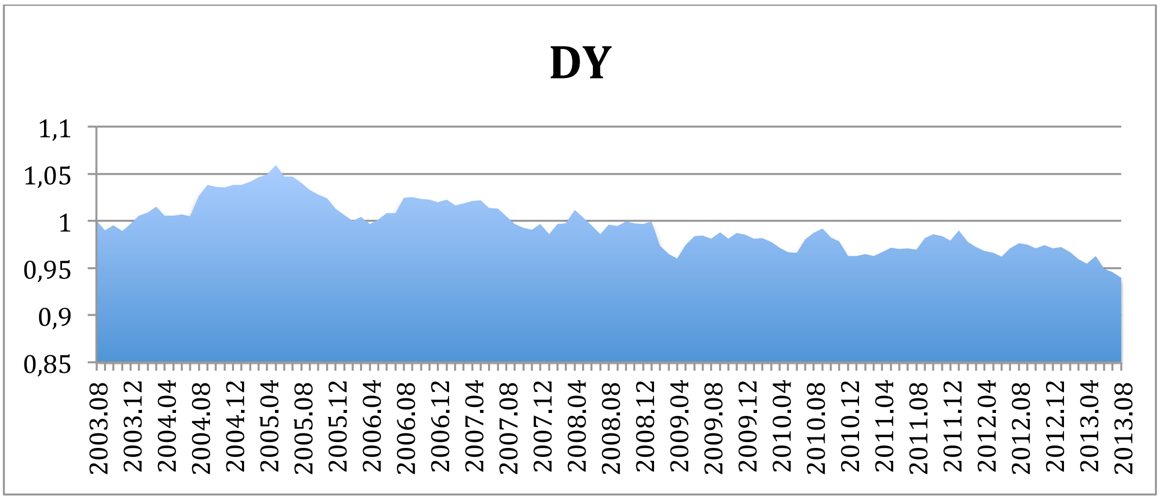
Factor	Average Slope	Std Dev	N	t
PTB	0,00005438884	0,00250616	121	0,23872295
CFP	-0,00008896612	0,00290585	121	-0,33677857
DY	-0,00049042810	0,00728019	121	-0,74101208
EY	0,00205287107	0,01198879	121	1,88355826
SP	0,00083094132	0,00961887	121	0,95025240
EBP	0,00371662810	0,00902142	121	4,53176023
S6	0,00099974380	0,00757412	121	1,45194264
S12	0,00072616281	0,00843025	121	0,94751548
S24	0,00079916281	0,00773946	121	1,13584026
E6	0,00112669835	0,00767142	121	1,61556550
E12	0,00109052893	0,00636579	121	1,88441991
E24	0,00076930909	0,00632657	121	1,33759696
D6	0,00070685785	0,00994482	121	0,78185796
D12	-0,00005303636	0,00878858	121	-0,06638159
D24	0,00225028099	0,00979346	121	2,52751236
DP12	0,00002601289	0,00945531	121	0,03026257
EP6	0,00046443719	0,00618260	121	0,82632067
EP12	0,00064998347	0,00649212	121	1,10130757
EP24	0,00062305372	0,00553419	121	1,23840855
PR	-0,00153401736	0,00785787	121	-2,14742651
ROE	0,00049214050	0,00784769	121	0,68982638
ROA	0,00082433058	0,00624132	121	1,45284019
STA	-0,00258102231	0,00404067	121	-7,02637831
DC	0,00161585322	0,00562297	121	3,16102883
OM	-0,00018762479	0,00782730	121	-0,26367616
CXS	0,00304124793	0,00529836	121	6,31398184
MOM1	-0,00063148760	0,01314934	121	-0,52826705
MOM3	0,00084270248	0,01513208	121	0,61258762
MOM6	0,00076294215	0,01793311	121	0,46798150
MOM12	0,00111314050	0,01876290	121	0,65259348
MOM24	0,00166597521	0,01762296	121	1,03987789
LNP	-0,00003959504	0,00241278	121	-0,18051632
LNMV	-0,00041910983	0,00288108	121	-1,60016716
LNEV	-0,00047225124	0,00286333	121	-1,81423633
TVO6	0,00150301074	0,00744388	121	2,22103449
TVO12	0,00124560248	0,00710200	121	1,92926244
TVO24	0,00155577736	0,00718484	121	2,38189680
STD	0,00003290909	0,00807376	121	0,04483663
VOL	-0,00024078025	0,00708981	121	-0,37357580
BET	0,00060137603	0,02005306	121	0,32988160
ITBT	0,00028027273	0,00768502	121	0,40116998
DE	-0,00010559000	0,00237053	121	-0,48997088
DA	0,00005923636	0,00541192	121	0,12040080
EM	0,00313439669	0,01243378	121	2,77295868

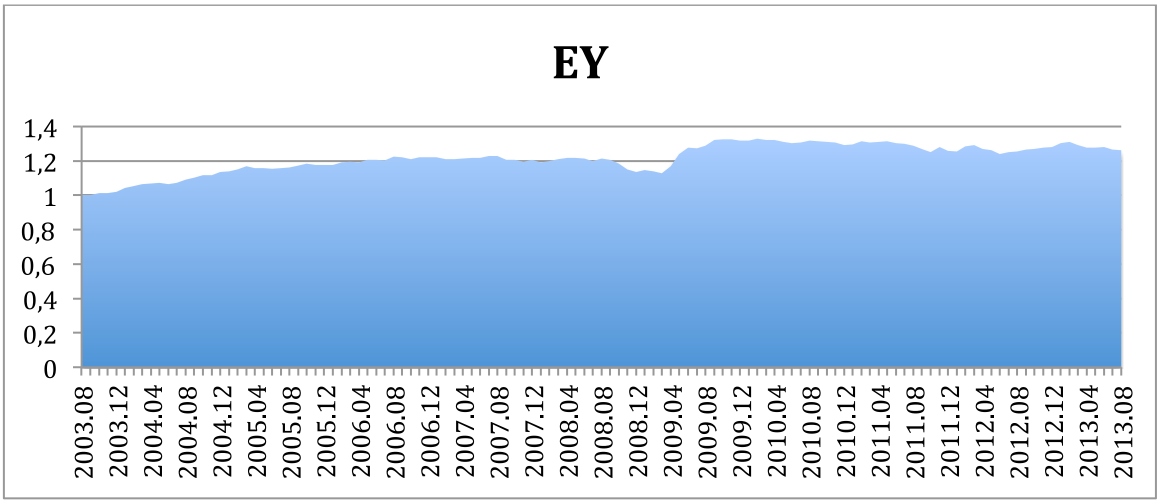
Appendix J: Evolution of the cumulative payoffs to each factor

Value Factors:





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2005.04
2005.08
2005.12
2006.04
2006.08
2006.12
2007.04
2007.08
2007.12
2008.04
2008.08
2008.12
2009.04
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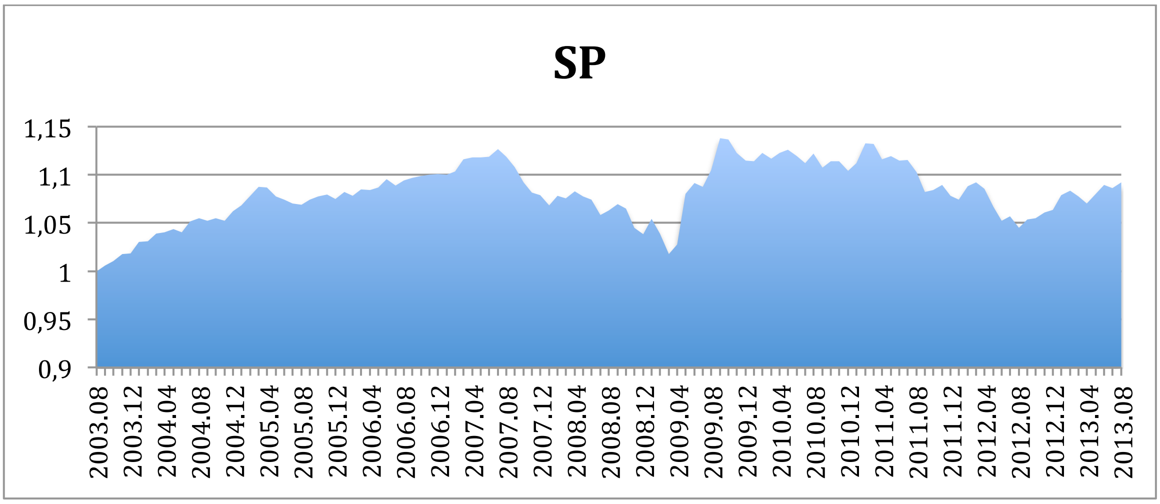
2012.12
2013.04
2013.08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1
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2005.12
2006.04
2006.08
2006.12
2007.04
2007.08
2007.12
2008.04
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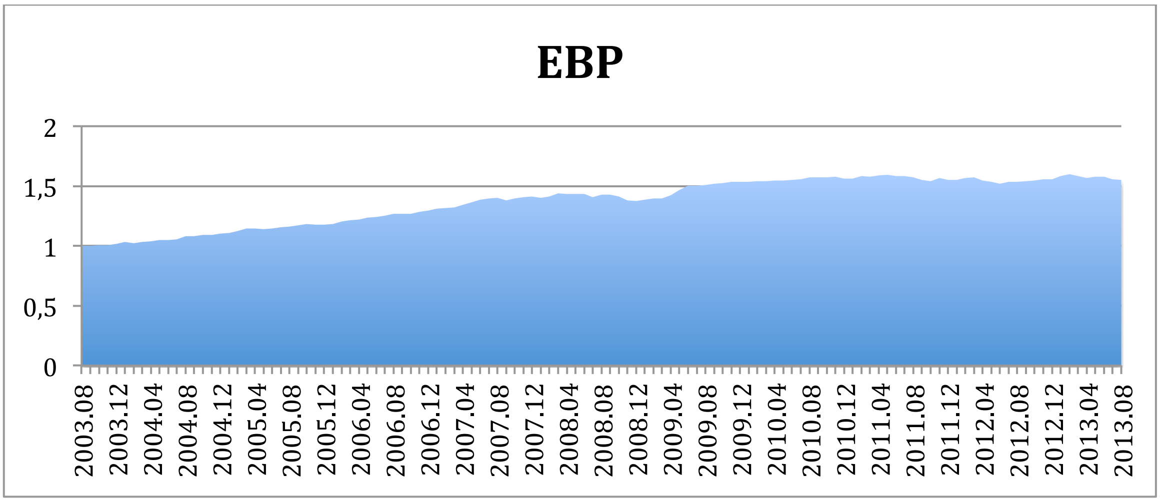
2012.12
2013.04
2013.08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2006.04
2006.08
2006.12
2007.04
2007.08
2007.12
2008.04
2008.08
2008.12
2009.04
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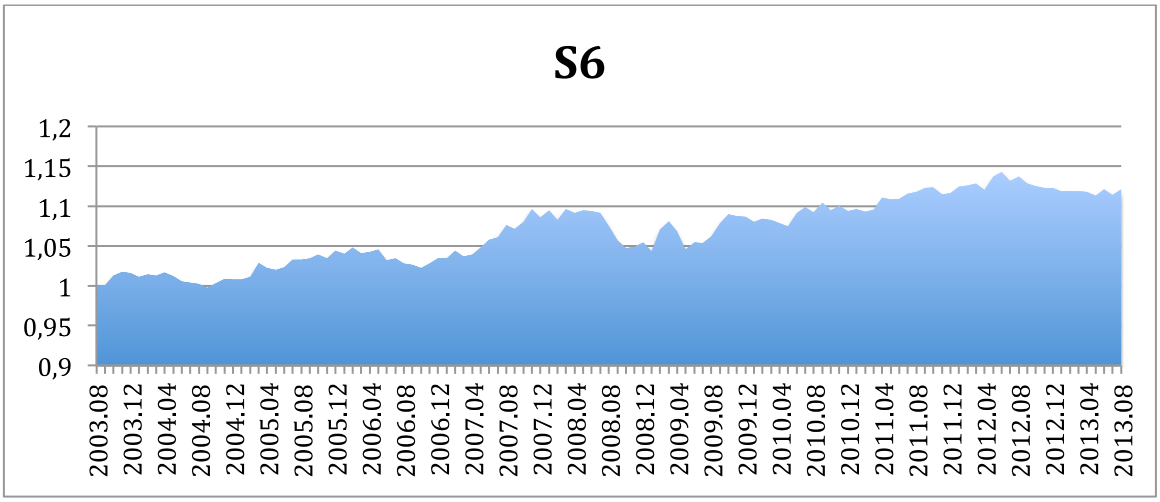
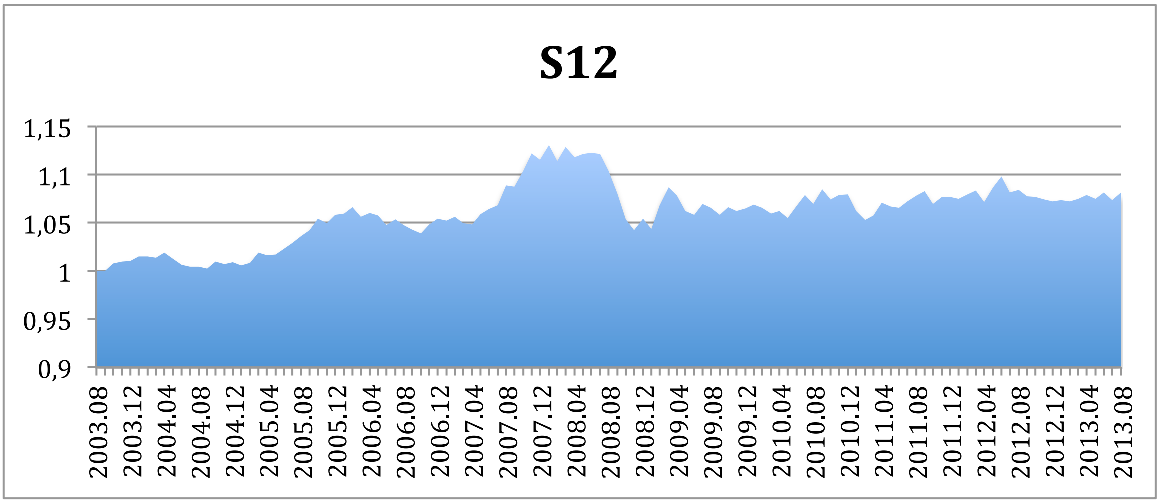
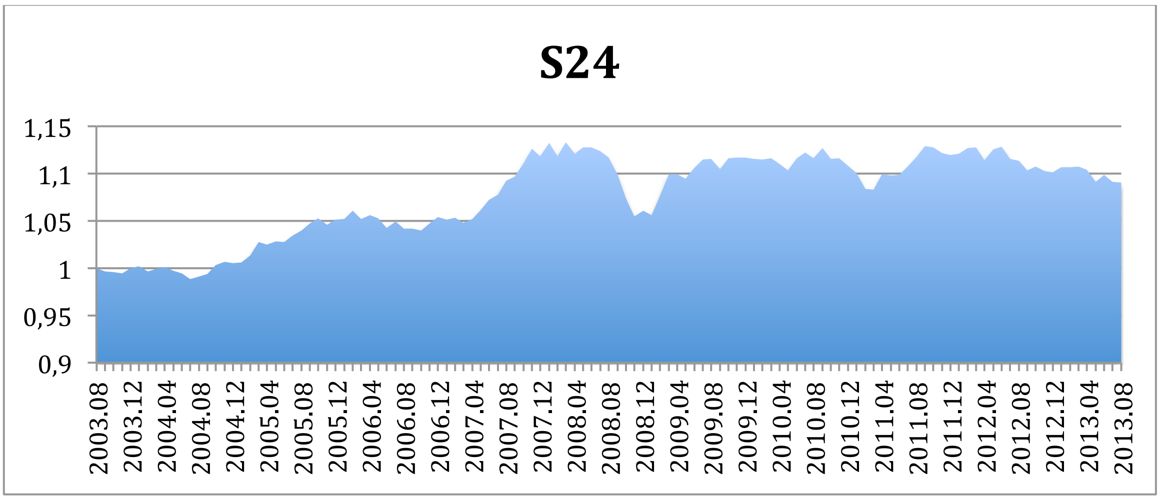
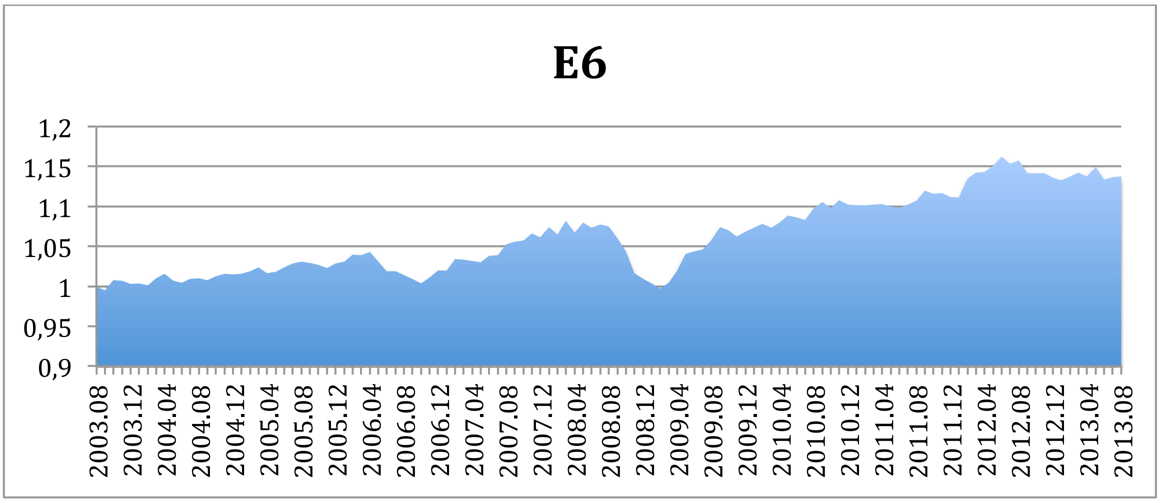
2013.04
2013.08

Growth Factors:





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2004.04
2004.08
2004.12
2005.04
2005.08
2005.12
2006.04
2006.08
2006.12
2007.04
2007.08
2007.12
2008.04
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2009.04
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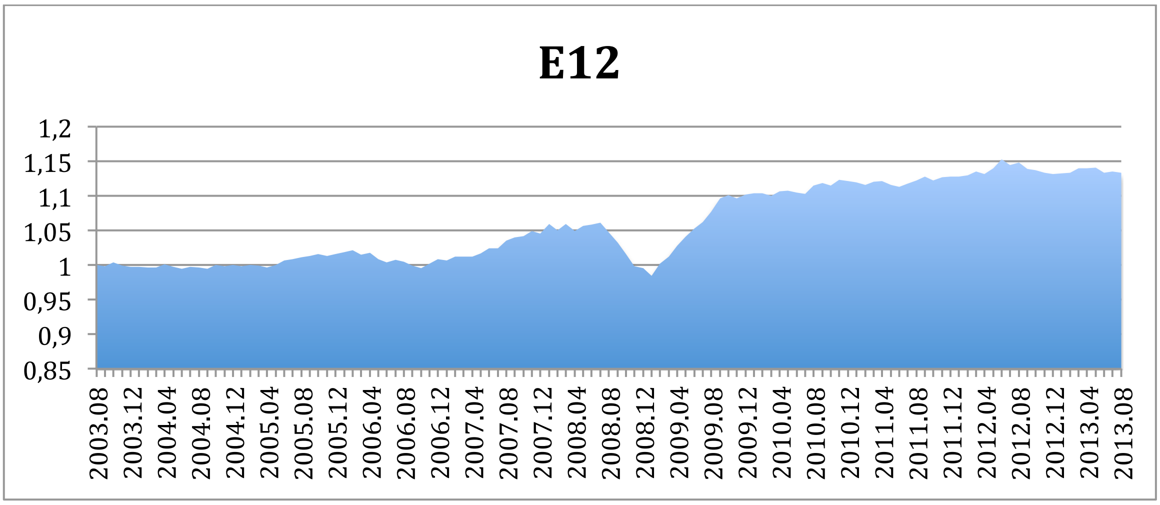
2012.12
2013.04
2013.08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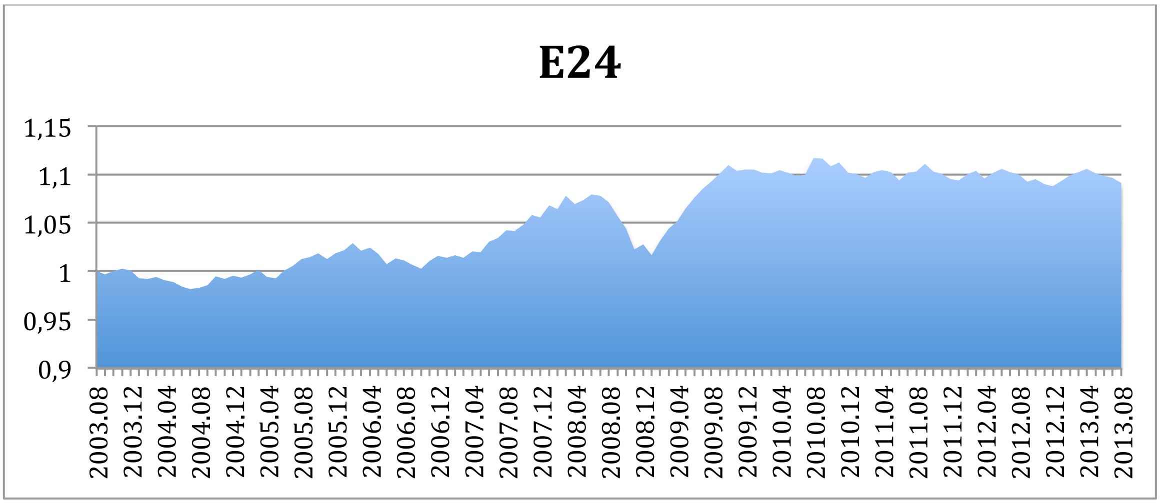
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2006.04
2006.08
2006.12
2007.04
2007.08
2007.12
2008.04
2008.08
2008.12
2009.04
2009.08
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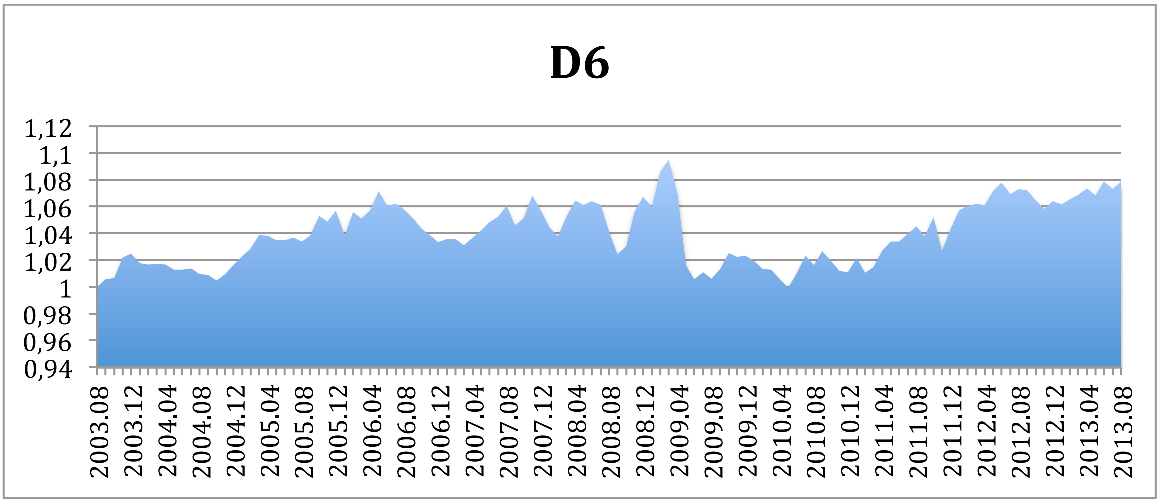
2013.08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2006.08
2006.12
2007.04
2007.08
2007.12
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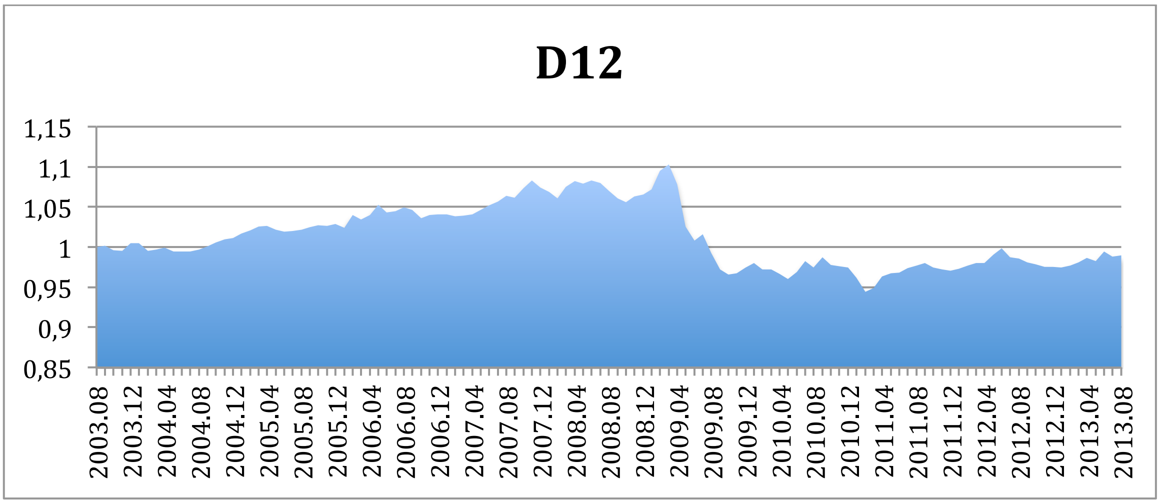
2013.08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2006.08
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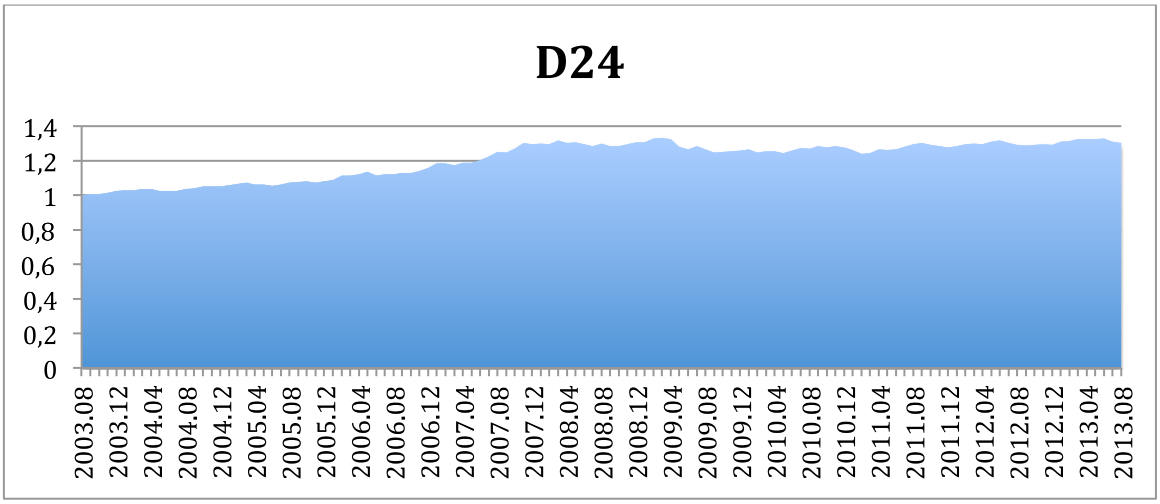
2013.08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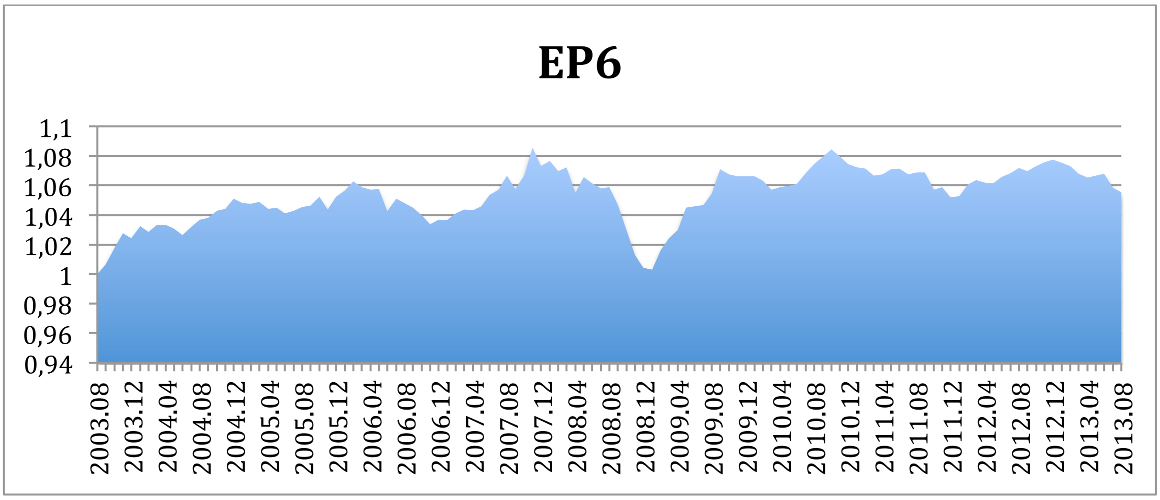
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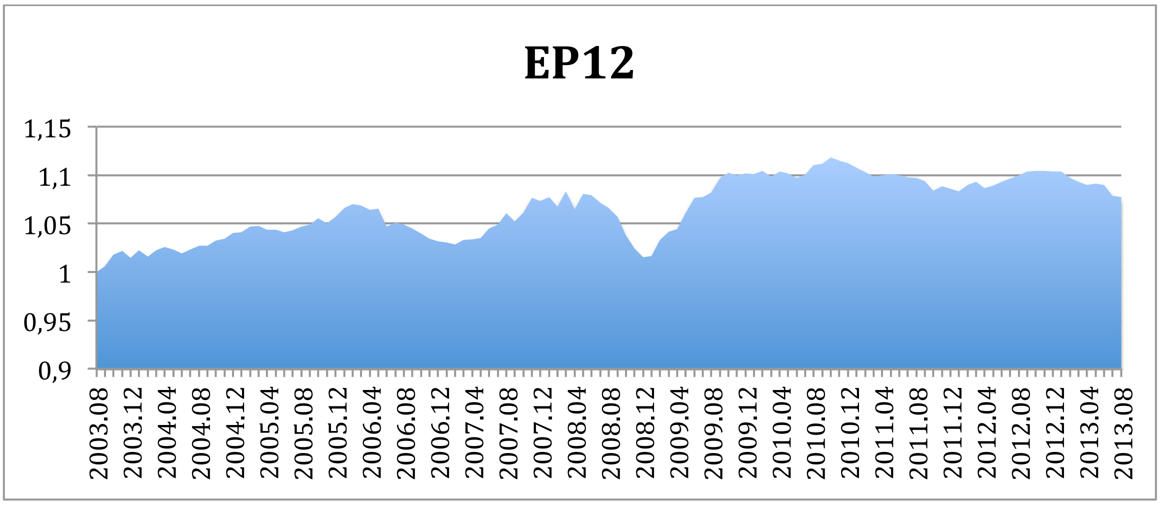
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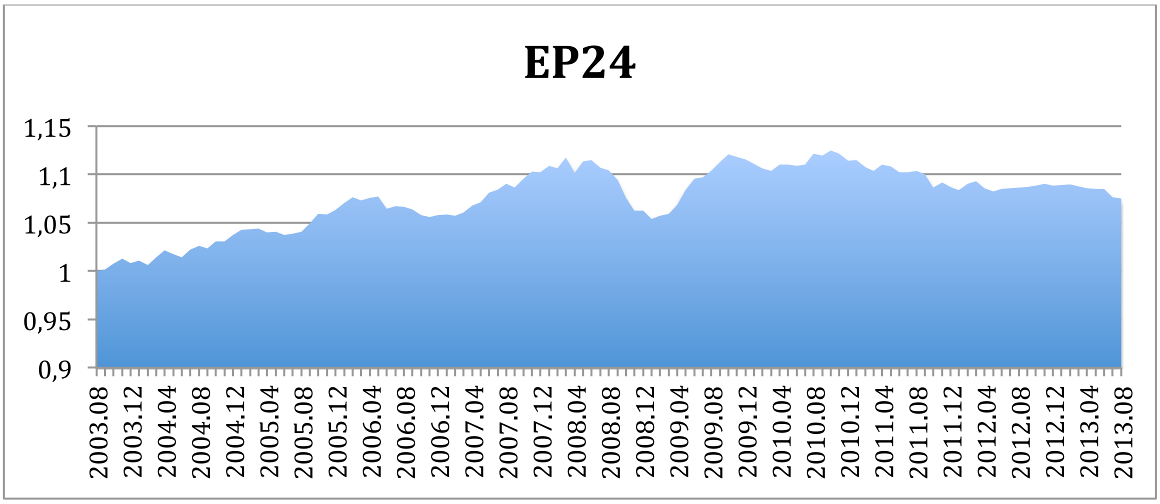
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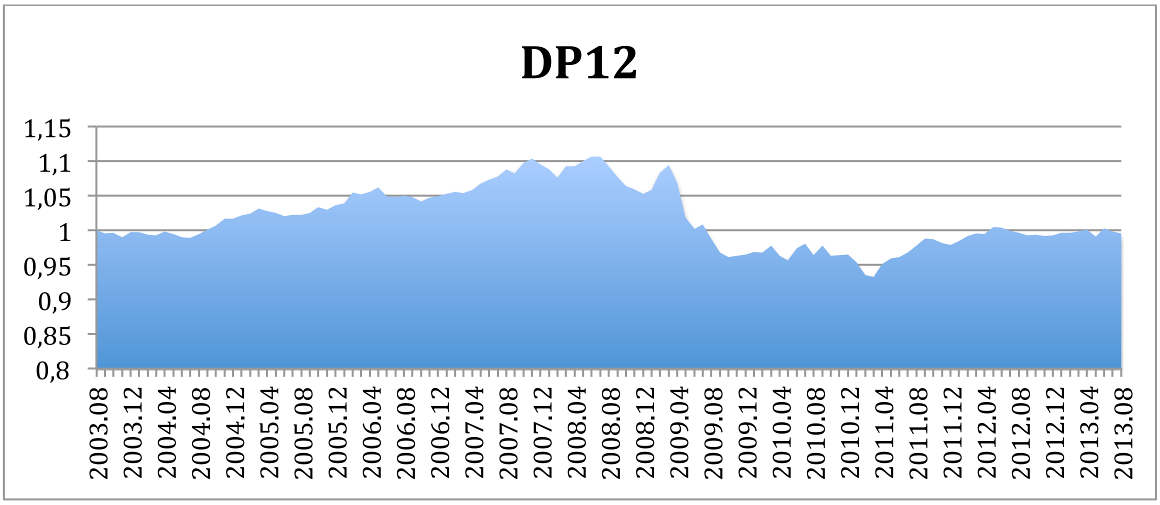
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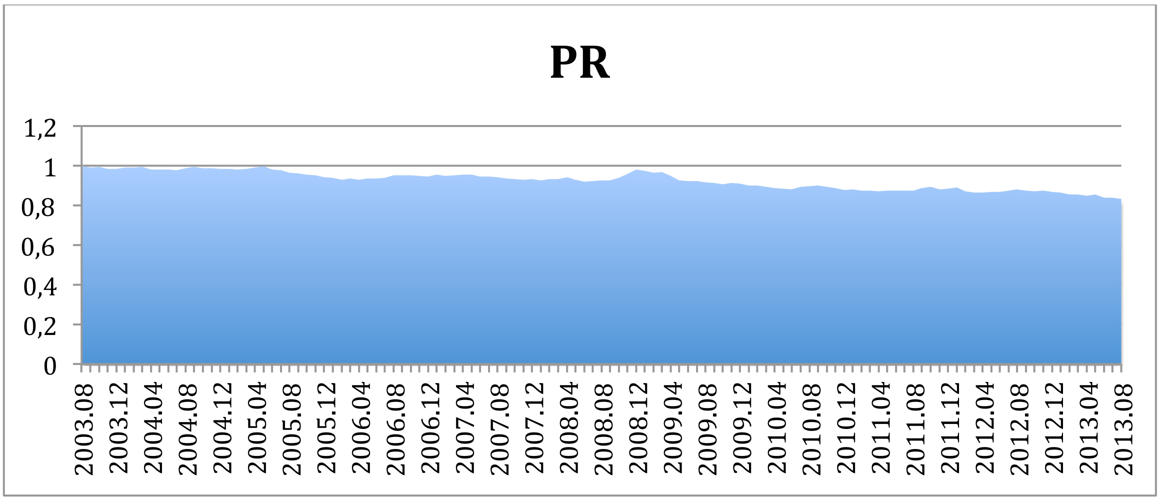
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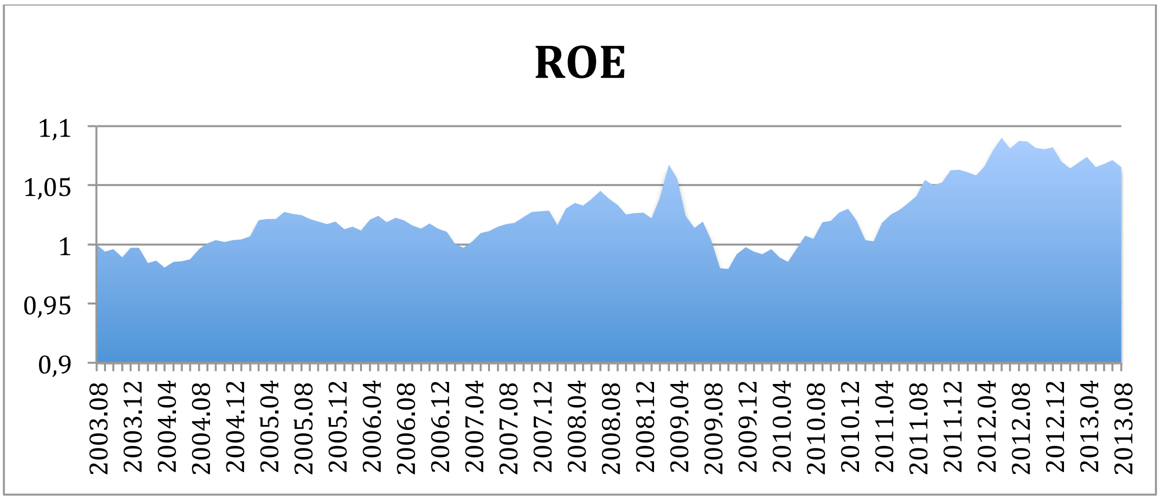
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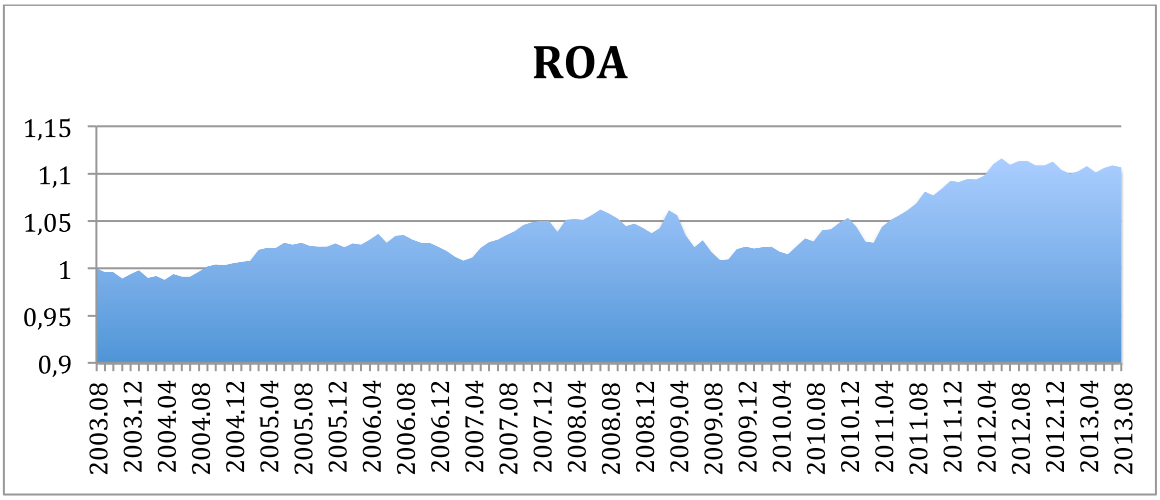
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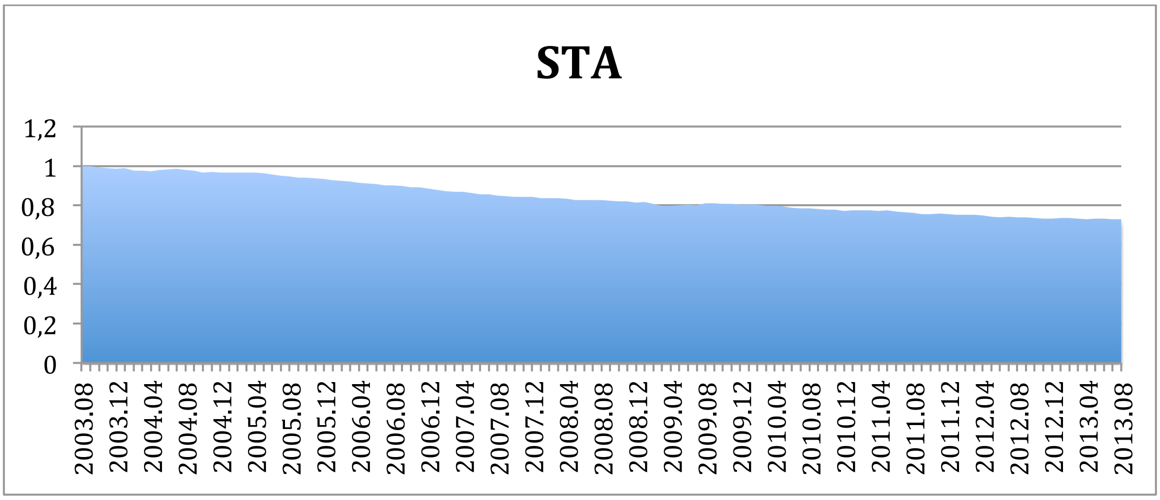
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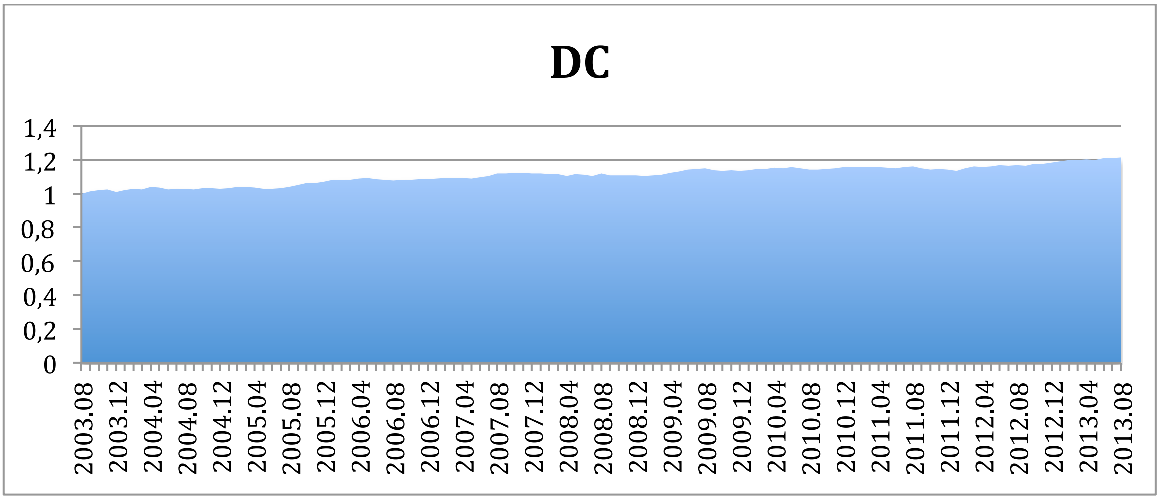
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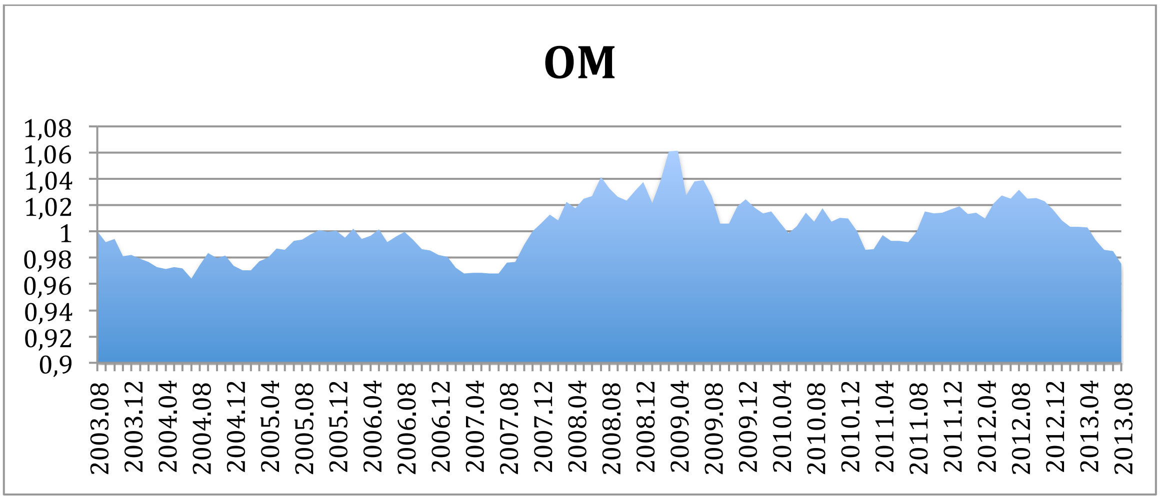
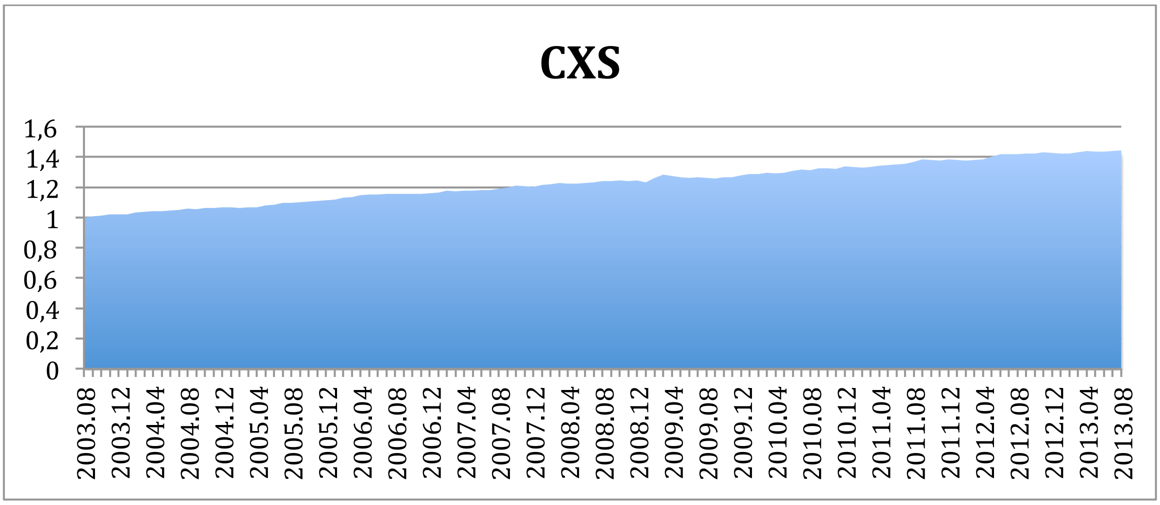
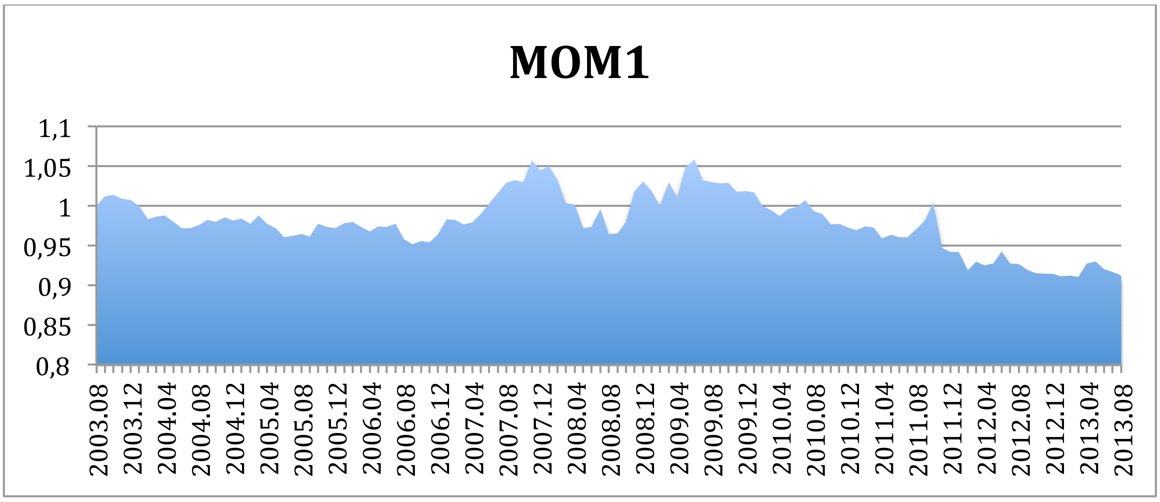
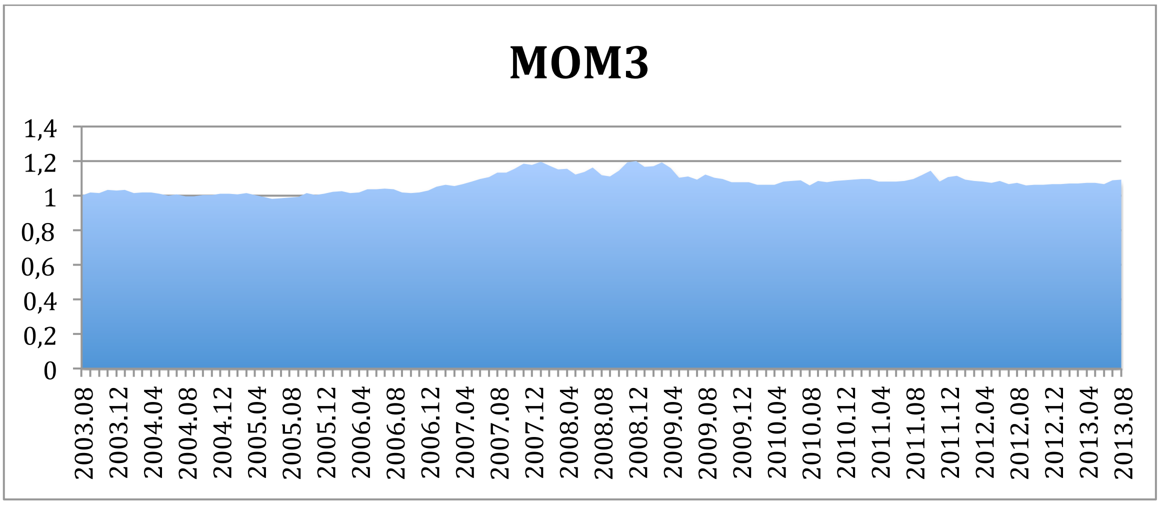




Momentum Factors:

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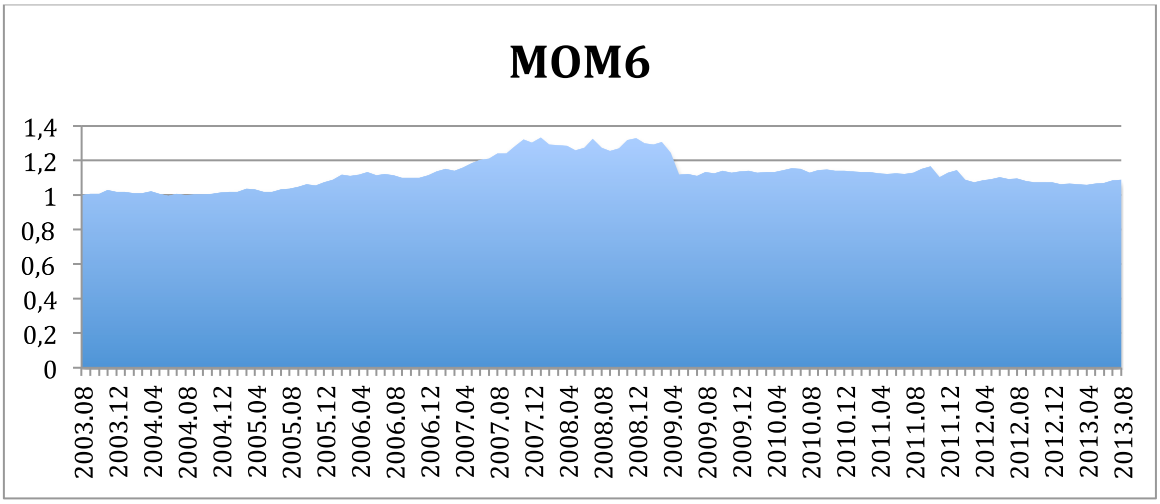
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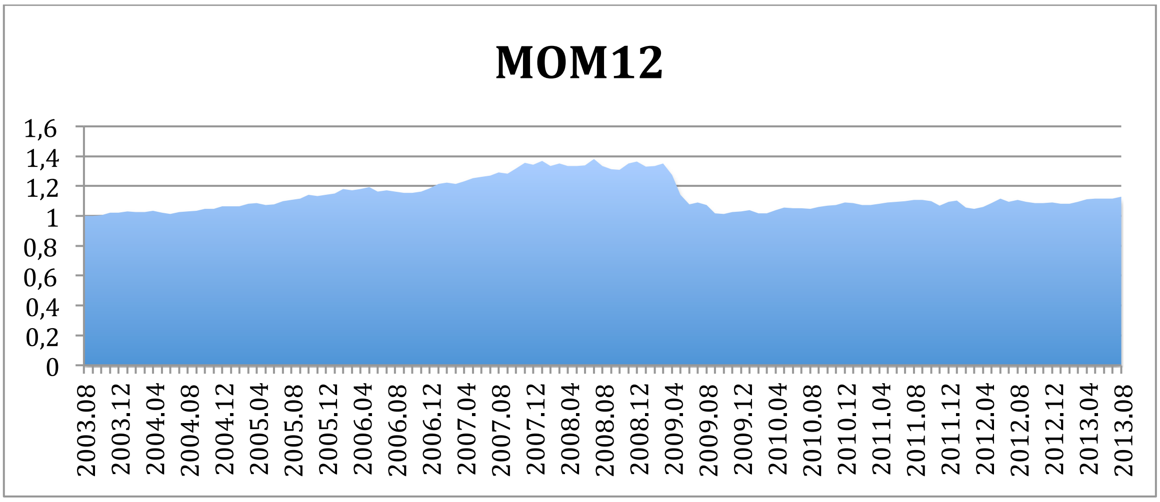
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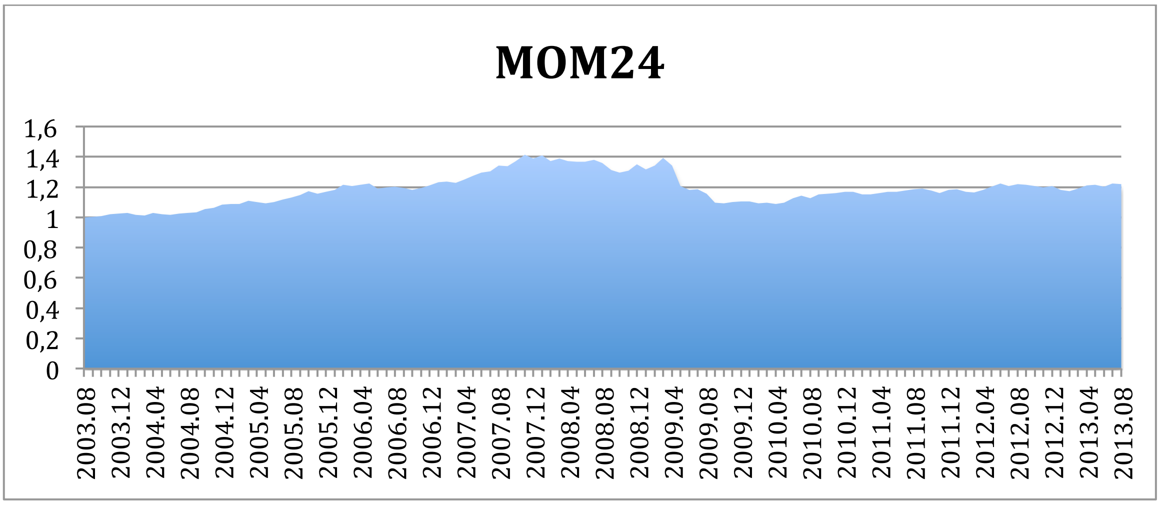

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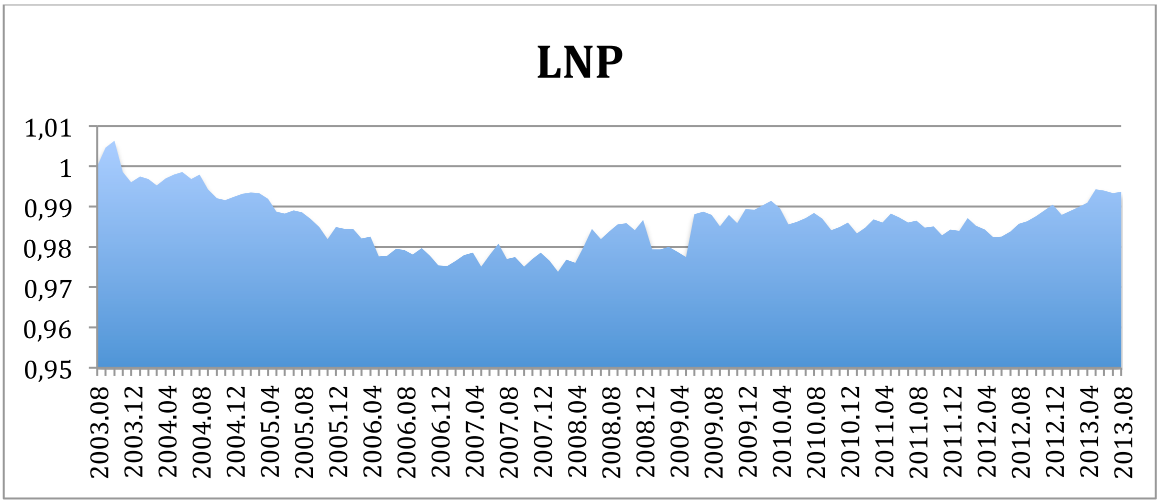

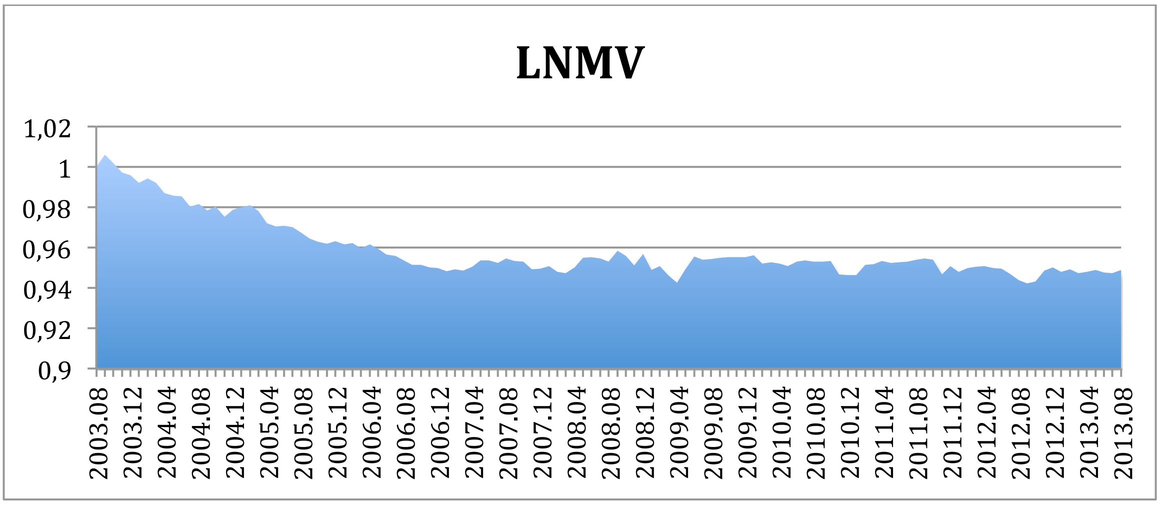

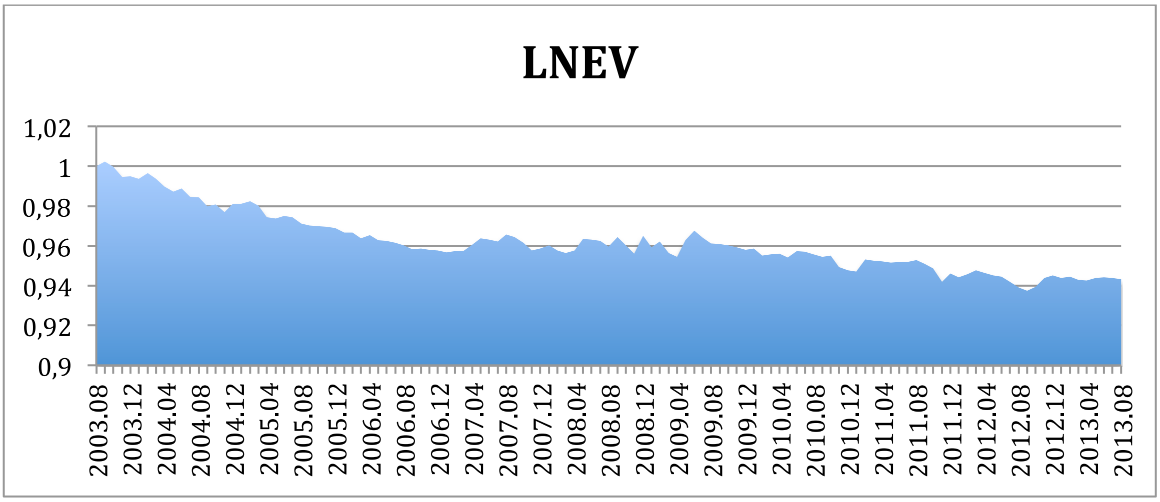
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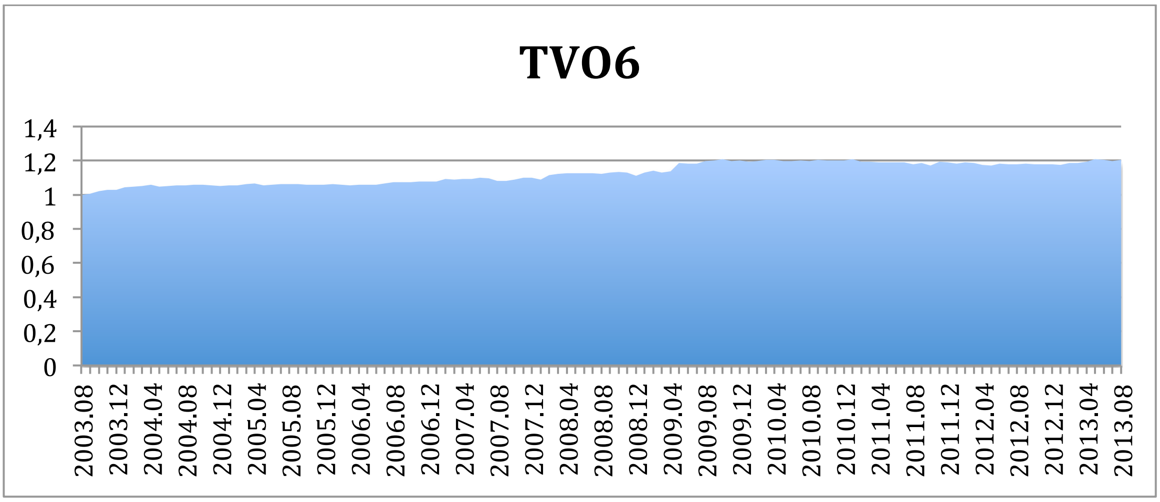
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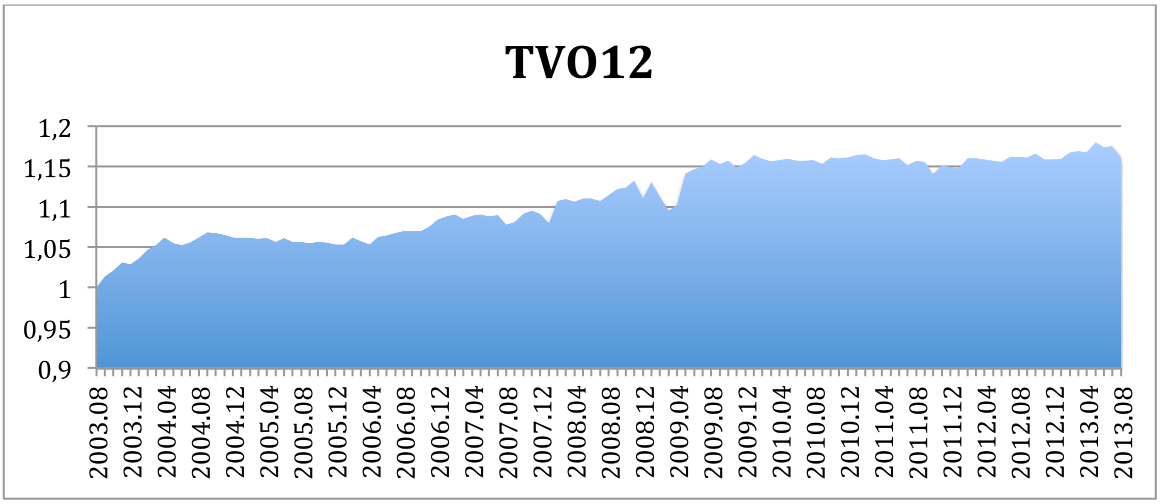
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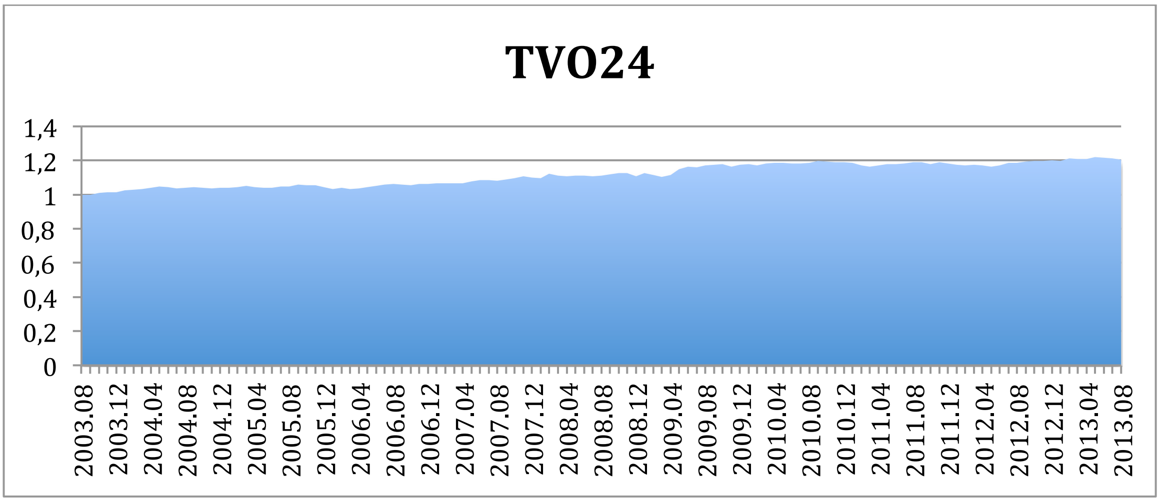

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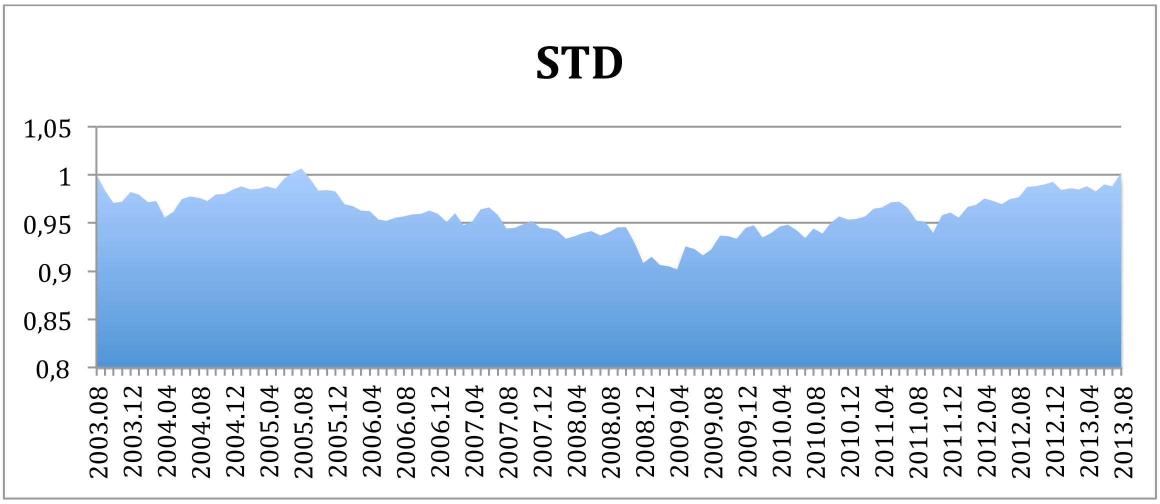
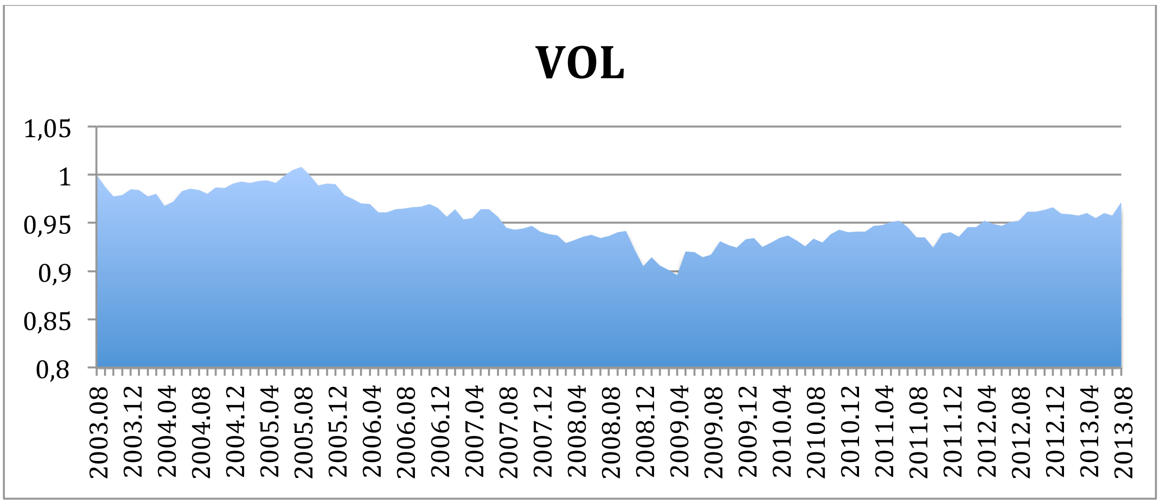
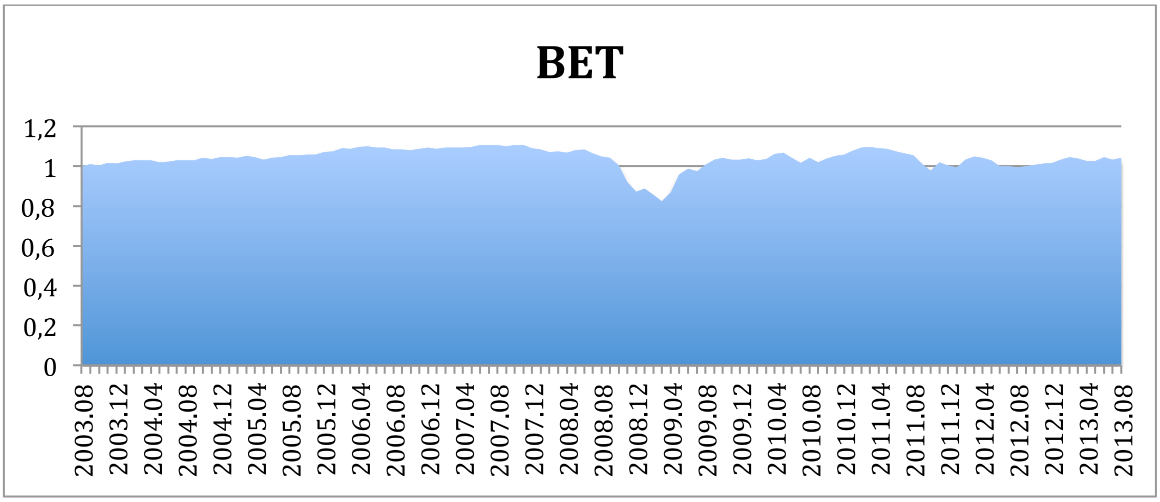
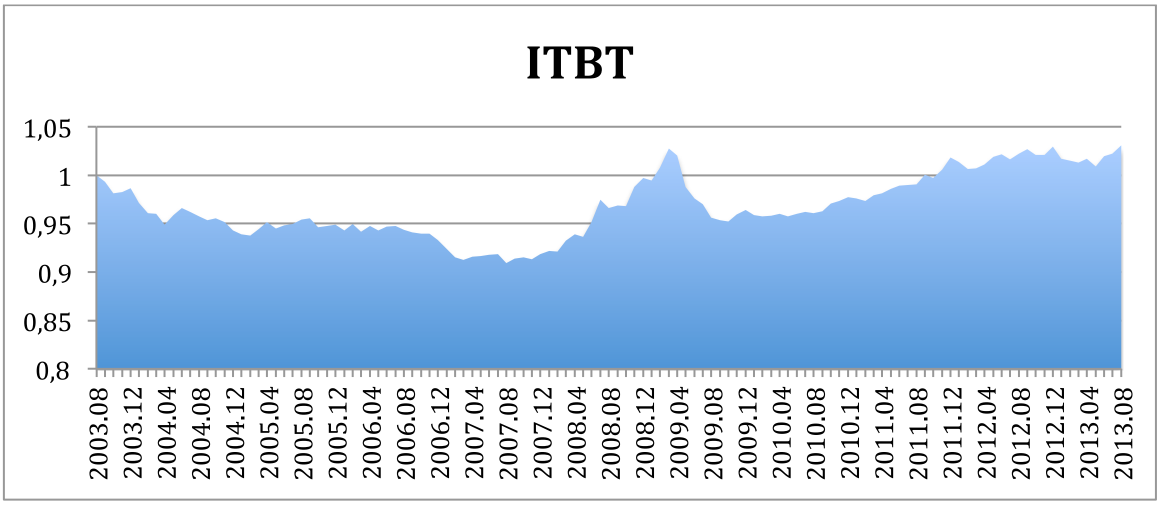
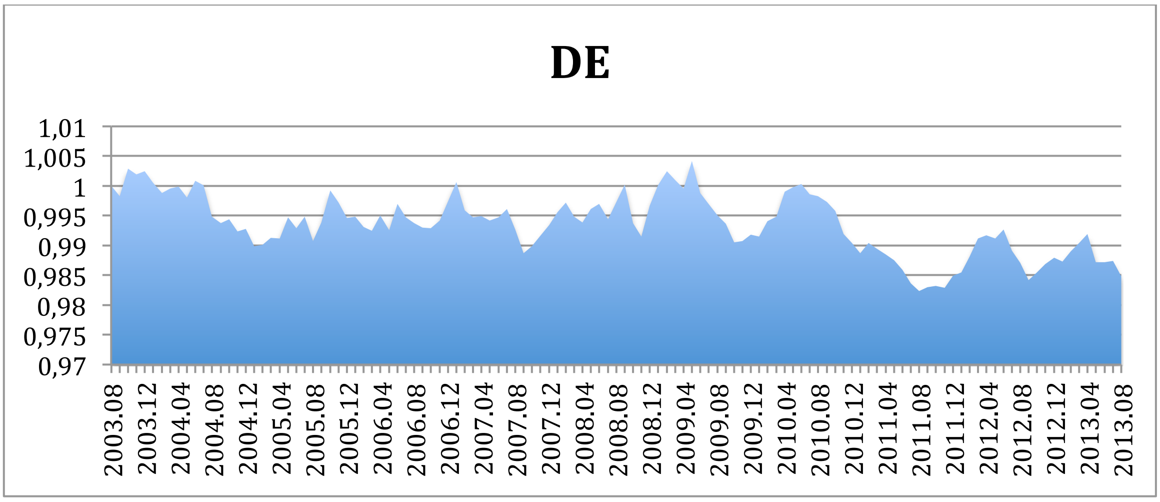


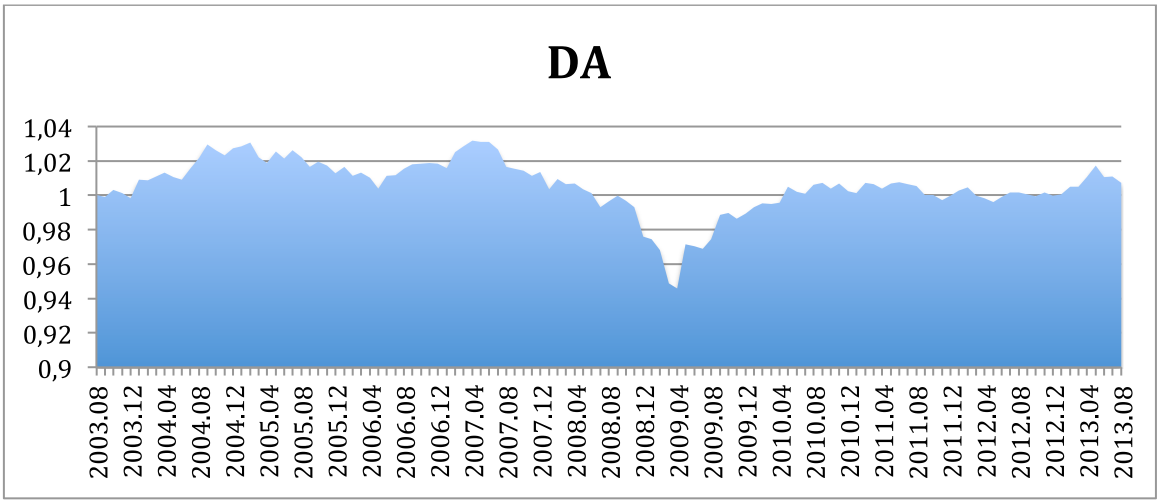




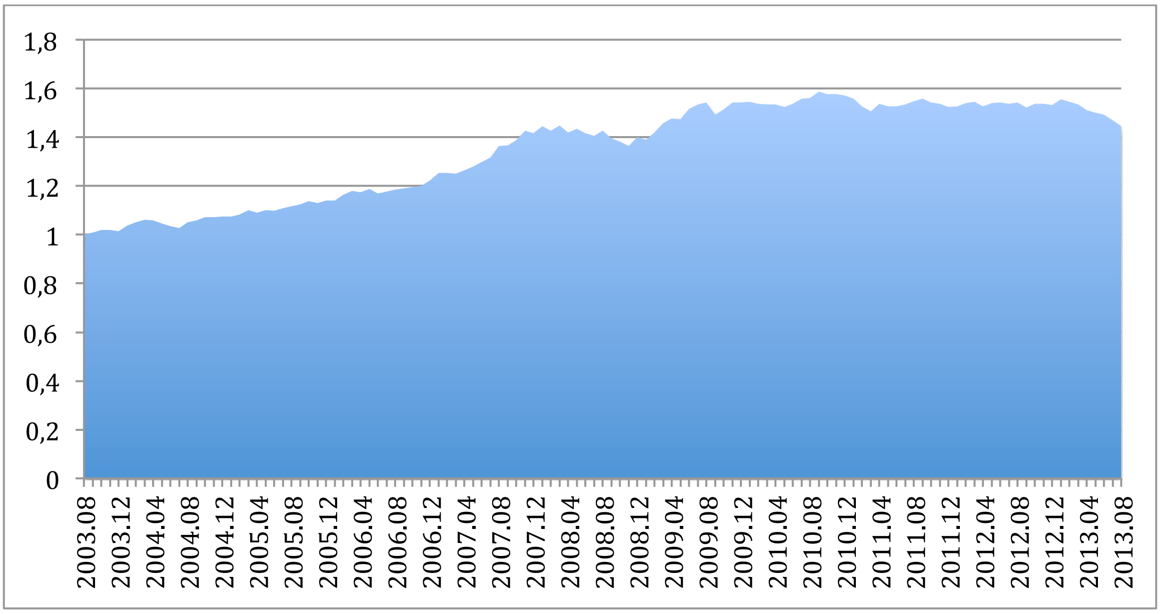
Leverage Factors:







Leverage Factors:



Appendix K: Total Cumulative Payoff over 10-year Period for each Factor

Factor	Total Cumulative Payoff
EBP	55%
EM	44%
CXS	44%
D24	30%
EY	26%
MOM24	22%
DC	21%
TVO24	20%
TVO6	20%
TVO12	16%
E6	14%
E12	13%
MOM12	13%
S6	12%
ROA	11%
MOM3	9%
SP	9%
E24	9%
S24	9%
MOM6	9%
S12	8%
D6	8%
EP12	8%
EP24	8%
ROE	7%
EP6	6%
BET	4%
ITBT	3%
PTB	1%
DA	1%
STD	0%
DP12	0%
LNP	-1%
CFP	-1%
D12	-1%
DE	-2%
OM	-2%
VOL	-3%
LNMV	-5%
LNEV	-6%
DY	-6%
MOM1	-9%
PR	-17%
STA	-27%

Appendix L: Correlation Matrices for each of the Styles and Combined

Value Correlation

	PTB	CFP	DY	EY	SP	EBP
PTB	1,00					
CFP	0,24	1,00				
DY	0,00	-0,04	1,00			
EY	0,06	0,12	0,37	1,00		
SP	0,11	0,14	0,27	0,75	1,00	
EBP	0,04	0,06	0,29	0,80	0,54	1,00

Momentum Correlation

	MOM1	MOM3	MOM6	MOM12	MOM24
MOM1	1,00				
MOM3	0,64	1,00			
MOM6	0,44	0,86	1,00		
MOM12	0,23	0,63	0,82	1,00	
MOM24	0,18	0,58	0,74	0,87	1,00

Size and Liquidity Correlation

	LNP	LNMV	LNEV	TVO6	TVO12	TVO24
LNP	1,00					
LNMV	0,38	1,00				
LNEV	0,32	0,91	1,00			
TVO6	-0,06	-0,12	-0,11	1,00		
TVO12	-0,09	-0,09	-0,08	0,67	1,00	
TVO24	-0,03	-0,04	-0,03	0,65	0,67	1,00

Risk Correlation

	STD	VOL	BET
STD	1,00		
VOL	0,98	1,00	
BET	0,55	0,58	1,00

Leverage and Emerging Market Correlation

	ITBT	DE	DA	EM
ITBT	1,00			
DE	-0,05	1,00		
DA	-0,60	0,09	1,00	
EM	-0,22	-0,02	-0,34	1,00

Growth Correlation

	S6	S12	S24	E6	E12	E24	D6	D12	D24	DP12	EP6	EP12	EP24	PR	ROE	ROA	STA	DC	OM	CXS
S6	1,00																			
S12	0,77	1,00																		
S24	0,72	0,85	1,00																	
E6	0,30	0,37	0,41	1,00																
E12	0,49	0,58	0,57	0,78	1,00															
E24	0,50	0,59	0,68	0,68	0,82	1,00														
D6	0,67	0,43	0,33	-0,23	-0,07	0,04	1,00													
D12	0,49	0,60	0,49	-0,16	-0,08	0,05	0,71	1,00												
D24	0,51	0,61	0,60	0,10	0,10	0,31	0,50	0,73	1,00											
DP12	0,57	0,64	0,62	-0,04	0,01	0,13	0,63	0,89	0,70	1,00										
EP6	0,40	0,45	0,47	0,59	0,58	0,58	0,01	0,01	0,27	0,10	1,00									
EP12	0,40	0,45	0,49	0,56	0,62	0,61	-0,01	-0,01	0,21	0,08	0,87	1,00								
EP24	0,30	0,41	0,48	0,57	0,62	0,67	-0,09	-0,08	0,24	-0,01	0,77	0,84	1,00							
PR	-0,02	-0,19	-0,18	-0,41	-0,42	-0,35	0,28	0,19	0,11	0,11	-0,37	-0,39	-0,43	1,00						
ROE	0,40	0,54	0,51	-0,09	0,05	0,10	0,48	0,74	0,46	0,72	-0,03	-0,01	-0,11	0,25	1,00					
ROA	0,41	0,57	0,51	0,00	0,10	0,12	0,44	0,71	0,45	0,71	0,07	0,08	-0,02	0,15	0,93	1,00				
STA	-0,39	-0,45	-0,39	-0,08	-0,20	-0,21	-0,27	-0,38	-0,44	-0,44	-0,09	-0,02	-0,02	-0,08	-0,41	-0,34	1,00			
DC	0,15	0,28	0,27	0,27	0,22	0,24	-0,10	-0,01	0,25	0,07	0,36	0,39	0,43	-0,50	-0,14	-0,06	-0,12	1,00		
OM	0,48	0,56	0,58	-0,01	0,19	0,23	0,42	0,60	0,49	0,62	0,02	0,09	0,02	0,34	0,75	0,70	-0,48	-0,03	1,00	
CXS	0,40	0,51	0,41	0,05	0,21	0,24	0,31	0,44	0,41	0,45	0,13	0,04	0,04	0,06	0,49	0,42	-0,70	0,06	0,48	1,00

Complete Correlation (I)

	PTB	CFP	DY	EY	SP	EBP	S6	S12	S24	E6	E12	E24	D6	D12	D24	DP12
PTB	1,00	0,24	0,00	0,06	0,11	0,04	-0,06	-0,09	-0,10	-0,14	-0,14	-0,07	-0,01	-0,01	0,00	-0,04
CFP	0,24	1,00	-0,04	0,12	0,14	0,06	-0,17	-0,10	-0,10	0,02	0,03	0,00	-0,14	-0,14	-0,05	-0,15
DY	0,00	-0,04	1,00	0,37	0,27	0,29	-0,29	-0,38	-0,24	-0,10	-0,28	-0,20	-0,22	-0,22	-0,15	-0,22
EY	0,06	0,12	0,37	1,00	0,75	0,80	-0,16	-0,12	0,02	0,30	0,20	0,27	-0,44	-0,42	-0,17	-0,33
SP	0,11	0,14	0,27	0,75	1,00	0,54	-0,37	-0,45	-0,36	0,15	-0,01	0,01	-0,48	-0,62	-0,46	-0,59
EBP	0,04	0,06	0,29	0,80	0,54	1,00	0,03	0,09	0,24	0,25	0,21	0,36	-0,25	-0,14	0,14	-0,07
S6	-0,06	-0,17	-0,29	-0,16	-0,37	0,03	1,00	0,77	0,72	0,30	0,49	0,50	0,67	0,49	0,51	0,57
S12	-0,09	-0,10	-0,38	-0,12	-0,45	0,09	0,77	1,00	0,85	0,37	0,58	0,59	0,43	0,60	0,61	0,64
S24	-0,10	-0,10	-0,24	0,02	-0,36	0,24	0,72	0,85	1,00	0,41	0,57	0,68	0,33	0,49	0,60	0,62
E6	-0,14	0,02	-0,10	0,30	0,15	0,25	0,30	0,37	0,41	1,00	0,78	0,68	-0,23	-0,16	0,10	-0,04
E12	-0,14	0,03	-0,28	0,20	-0,01	0,21	0,49	0,58	0,57	0,78	1,00	0,82	-0,07	-0,08	0,10	0,01
E24	-0,07	0,00	-0,20	0,27	0,01	0,36	0,50	0,59	0,68	0,68	0,82	1,00	0,04	0,05	0,31	0,13
D6	-0,01	-0,14	-0,22	-0,44	-0,48	-0,25	0,67	0,43	0,33	-0,23	-0,07	0,04	1,00	0,71	0,50	0,63
D12	-0,01	-0,14	-0,22	-0,42	-0,62	-0,14	0,49	0,60	0,49	-0,16	-0,08	0,05	0,71	1,00	0,73	0,89
D24	0,00	-0,05	-0,15	-0,17	-0,46	0,14	0,51	0,61	0,60	0,10	0,10	0,31	0,50	0,73	1,00	0,70
DP12	-0,04	-0,15	-0,22	-0,33	-0,59	-0,07	0,57	0,64	0,62	-0,04	0,01	0,13	0,63	0,89	0,70	1,00
EP6	0,08	0,05	-0,11	0,41	0,18	0,45	0,40	0,45	0,47	0,59	0,58	0,58	0,01	0,01	0,27	0,10
EP12	-0,06	0,00	-0,14	0,45	0,19	0,48	0,40	0,45	0,49	0,56	0,62	0,61	-0,01	-0,01	0,21	0,08
EP24	-0,07	0,07	-0,13	0,51	0,27	0,57	0,30	0,41	0,48	0,57	0,62	0,67	-0,09	-0,08	0,24	-0,01
PR	-0,01	-0,09	0,61	-0,35	-0,34	-0,24	-0,02	-0,19	-0,18	-0,41	-0,42	-0,35	0,28	0,19	0,11	0,11
ROE	-0,10	-0,13	-0,14	-0,44	-0,73	-0,19	0,40	0,54	0,51	-0,09	0,05	0,10	0,48	0,74	0,46	0,72
ROA	-0,16	-0,15	-0,14	-0,34	-0,67	-0,15	0,41	0,57	0,51	0,00	0,10	0,12	0,44	0,71	0,45	0,71
STA	-0,21	-0,08	0,27	0,36	0,55	0,21	-0,39	-0,45	-0,39	-0,08	-0,20	-0,21	-0,27	-0,38	-0,44	-0,44
DC	-0,05	0,11	-0,41	0,26	0,13	0,25	0,15	0,28	0,27	0,27	0,22	0,24	-0,10	-0,01	0,25	0,07
OM	-0,18	-0,08	-0,06	-0,36	-0,81	-0,13	0,48	0,56	0,58	-0,01	0,19	0,23	0,42	0,60	0,49	0,62
CXS	0,07	-0,10	-0,35	-0,42	-0,59	-0,26	0,40	0,51	0,41	0,05	0,21	0,24	0,31	0,44	0,41	0,45
MOM1	0,03	0,06	0,03	-0,24	-0,11	-0,20	0,17	0,05	0,09	-0,01	0,02	0,05	0,20	-0,01	0,05	-0,02
MOM3	0,00	-0,07	-0,23	-0,53	-0,42	-0,36	0,40	0,24	0,17	-0,13	-0,02	-0,01	0,54	0,32	0,27	0,29
MOM6	-0,01	-0,23	-0,27	-0,61	-0,55	-0,36	0,53	0,36	0,25	-0,13	-0,01	0,01	0,63	0,48	0,39	0,45
MOM12	-0,01	-0,12	-0,32	-0,66	-0,68	-0,36	0,42	0,48	0,27	-0,11	-0,04	-0,01	0,60	0,67	0,55	0,59
MOM24	-0,02	-0,17	-0,32	-0,54	-0,71	-0,21	0,56	0,63	0,48	-0,02	0,07	0,15	0,64	0,75	0,64	0,72
LNP	-0,32	-0,13	-0,04	0,01	-0,03	0,10	0,09	0,05	0,09	0,07	0,11	0,16	0,01	-0,05	-0,03	-0,01
LNMV	-0,14	0,04	-0,03	0,09	0,10	0,03	0,08	0,02	0,06	0,09	0,13	0,19	-0,02	-0,16	-0,06	-0,13
LNEV	0,00	0,17	-0,05	0,14	0,19	0,09	0,03	0,03	0,05	0,07	0,13	0,16	-0,08	-0,19	-0,09	-0,16
TVO6	0,11	0,15	0,14	0,42	0,41	0,33	-0,14	-0,10	-0,10	0,20	0,13	0,09	-0,30	-0,24	-0,14	-0,26
TVO12	0,16	0,15	0,23	0,45	0,43	0,31	-0,39	-0,33	-0,29	0,11	-0,11	-0,09	-0,40	-0,34	-0,12	-0,36
TVO24	0,13	0,11	0,26	0,45	0,37	0,40	-0,24	-0,19	-0,09	0,12	0,05	0,05	-0,36	-0,27	-0,12	-0,29
STD	0,02	-0,05	0,03	0,26	0,33	0,20	-0,23	-0,21	-0,17	0,15	0,08	0,07	-0,35	-0,28	-0,35	-0,32
VOL	0,00	-0,05	0,07	0,31	0,39	0,21	-0,26	-0,23	-0,19	0,17	0,07	0,05	-0,39	-0,31	-0,38	-0,33
BET	-0,02	0,11	-0,04	0,74	0,71	0,56	-0,21	-0,12	-0,03	0,44	0,33	0,30	-0,52	-0,50	-0,28	-0,42
ITBT	-0,12	-0,19	-0,31	-0,55	-0,59	-0,41	0,19	0,19	0,09	-0,33	-0,14	-0,10	0,40	0,46	0,07	0,33
DE	-0,09	0,21	-0,06	0,08	0,11	0,07	-0,08	0,06	0,06	0,07	0,03	0,07	-0,12	-0,06	0,00	-0,04
DA	0,09	0,10	0,43	0,43	0,58	0,24	-0,36	-0,41	-0,39	0,20	0,04	-0,08	-0,43	-0,51	-0,39	-0,45
EM	-0,02	0,01	0,01	0,16	-0,28	0,38	0,45	0,59	0,72	0,29	0,34	0,48	0,15	0,30	0,66	0,39

Complete Correlation (II)

	EP6	EP12	EP24	PR	ROE	ROA	STA	DC	OM	CXS	MOM1	MOM3	MOM6	MOM12	MOM24
PTB	0,08	-0,06	-0,07	-0,01	-0,10	-0,16	-0,21	-0,05	-0,18	0,07	0,03	0,00	-0,01	-0,01	-0,02
CFP	0,05	0,00	0,07	-0,09	-0,13	-0,15	-0,08	0,11	-0,08	-0,10	0,06	-0,07	-0,23	-0,12	-0,17
DY	-0,11	-0,14	-0,13	0,61	-0,14	-0,14	0,27	-0,41	-0,06	-0,35	0,03	-0,23	-0,27	-0,32	-0,32
EY	0,41	0,45	0,51	-0,35	-0,44	-0,34	0,36	0,26	-0,36	-0,42	-0,24	-0,53	-0,61	-0,66	-0,54
SP	0,18	0,19	0,27	-0,34	-0,73	-0,67	0,55	0,13	-0,81	-0,59	-0,11	-0,42	-0,55	-0,68	-0,71
EBP	0,45	0,48	0,57	-0,24	-0,19	-0,15	0,21	0,25	-0,13	-0,26	-0,20	-0,36	-0,36	-0,36	-0,21
S6	0,40	0,40	0,30	-0,02	0,40	0,41	-0,39	0,15	0,48	0,40	0,17	0,40	0,53	0,42	0,56
S12	0,45	0,45	0,41	-0,19	0,54	0,57	-0,45	0,28	0,56	0,51	0,05	0,24	0,36	0,48	0,63
S24	0,47	0,49	0,48	-0,18	0,51	0,51	-0,39	0,27	0,58	0,41	0,09	0,17	0,25	0,27	0,48
E6	0,59	0,56	0,57	-0,41	-0,09	0,00	-0,08	0,27	-0,01	0,05	-0,01	-0,13	-0,13	-0,11	-0,02
E12	0,58	0,62	0,62	-0,42	0,05	0,10	-0,20	0,22	0,19	0,21	0,02	-0,02	-0,01	-0,04	0,07
E24	0,58	0,61	0,67	-0,35	0,10	0,12	-0,21	0,24	0,23	0,24	0,05	-0,01	0,01	-0,01	0,15
D6	0,01	-0,01	-0,09	0,28	0,48	0,44	-0,27	-0,10	0,42	0,31	0,20	0,54	0,63	0,60	0,64
D12	0,01	-0,01	-0,08	0,19	0,74	0,71	-0,38	-0,01	0,60	0,44	-0,01	0,32	0,48	0,67	0,75
D24	0,27	0,21	0,24	0,11	0,46	0,45	-0,44	0,25	0,49	0,41	0,05	0,27	0,39	0,55	0,64
DP12	0,10	0,08	-0,01	0,11	0,72	0,71	-0,44	0,07	0,62	0,45	-0,02	0,29	0,45	0,59	0,72
EP6	1,00	0,87	0,77	-0,37	-0,03	0,07	-0,09	0,36	0,02	0,13	0,01	-0,07	-0,03	-0,03	0,10
EP12	0,87	1,00	0,84	-0,39	-0,01	0,08	-0,02	0,39	0,09	0,04	-0,05	-0,14	-0,07	-0,08	0,05
EP24	0,77	0,84	1,00	-0,43	-0,11	-0,02	-0,02	0,43	0,02	0,04	-0,09	-0,17	-0,11	-0,09	0,04
PR	-0,37	-0,39	-0,43	1,00	0,25	0,15	-0,08	-0,50	0,34	0,06	0,24	0,30	0,32	0,28	0,24
ROE	-0,03	-0,01	-0,11	0,25	1,00	0,93	-0,41	-0,14	0,75	0,49	0,01	0,24	0,37	0,57	0,70
ROA	0,07	0,08	-0,02	0,15	0,93	1,00	-0,34	-0,06	0,70	0,42	-0,04	0,16	0,32	0,53	0,63
STA	-0,09	-0,02	-0,02	-0,08	-0,41	-0,34	1,00	-0,12	-0,48	-0,70	-0,08	-0,22	-0,32	-0,42	-0,52
DC	0,36	0,39	0,43	-0,50	-0,14	-0,06	-0,12	1,00	-0,03	0,06	-0,07	-0,05	-0,11	-0,04	0,09
OM	0,02	0,09	0,02	0,34	0,75	0,70	-0,48	-0,03	1,00	0,48	0,08	0,29	0,41	0,48	0,63
CXS	0,13	0,04	0,04	0,06	0,49	0,42	-0,70	0,06	0,48	1,00	0,03	0,26	0,37	0,46	0,56
MOM1	0,01	-0,05	-0,09	0,24	0,01	-0,04	-0,08	-0,07	0,08	0,03	1,00	0,64	0,44	0,23	0,18
MOM3	-0,07	-0,14	-0,17	0,30	0,24	0,16	-0,22	-0,05	0,29	0,26	0,64	1,00	0,86	0,63	0,58
MOM6	-0,03	-0,07	-0,11	0,32	0,37	0,32	-0,32	-0,11	0,41	0,37	0,44	0,86	1,00	0,82	0,74
MOM12	-0,03	-0,08	-0,09	0,28	0,57	0,53	-0,42	-0,04	0,48	0,46	0,23	0,63	0,82	1,00	0,87
MOM24	0,10	0,05	0,04	0,24	0,70	0,63	-0,52	0,09	0,63	0,56	0,18	0,58	0,74	0,87	1,00
LNP	0,01	0,17	0,11	-0,03	0,03	-0,01	0,04	0,19	0,15	-0,02	0,00	-0,01	-0,03	-0,12	0,01
LNMV	0,05	0,06	0,12	-0,06	-0,12	-0,15	-0,21	0,02	-0,08	0,16	0,14	0,07	-0,01	-0,13	-0,09
LNEV	0,04	0,06	0,14	-0,10	-0,17	-0,23	-0,24	0,05	-0,13	0,08	0,12	-0,02	-0,10	-0,17	-0,10
TVO6	0,26	0,24	0,24	-0,26	-0,30	-0,24	0,21	0,03	-0,32	-0,15	-0,10	-0,29	-0,38	-0,39	-0,40
TVO12	0,14	0,10	0,17	-0,25	-0,45	-0,38	0,29	0,13	-0,40	-0,29	-0,06	-0,29	-0,38	-0,37	-0,45
TVO24	0,18	0,14	0,23	-0,20	-0,32	-0,26	0,18	0,07	-0,26	-0,20	0,01	-0,23	-0,33	-0,39	-0,40
STD	0,13	0,06	0,08	-0,39	-0,16	-0,09	0,32	-0,25	-0,40	-0,21	-0,24	-0,38	-0,38	-0,32	-0,38
VOL	0,14	0,08	0,09	-0,40	-0,20	-0,13	0,33	-0,22	-0,45	-0,24	-0,24	-0,42	-0,42	-0,37	-0,43
BET	0,42	0,42	0,53	-0,72	-0,52	-0,40	0,35	0,29	-0,54	-0,39	-0,24	-0,47	-0,52	-0,53	-0,53
ITBT	-0,33	-0,29	-0,34	0,18	0,62	0,57	-0,17	-0,35	0,48	0,28	-0,01	0,21	0,34	0,43	0,40
DE	0,06	0,01	0,10	-0,12	-0,06	-0,17	-0,06	0,03	-0,10	0,01	0,00	-0,12	-0,19	-0,07	-0,06
DA	0,13	0,09	0,11	-0,11	-0,53	-0,46	0,36	-0,09	-0,57	-0,35	-0,02	-0,28	-0,40	-0,44	-0,56
EM	0,45	0,46	0,46	0,07	0,31	0,29	-0,42	0,42	0,52	0,32	0,09	0,14	0,19	0,23	0,42

Complete Correlation (III)

	LNP	LNMV	LNEV	TVO6	TVO12	TVO24	STD	VOL	BET	ITBT	DE	DA	EM
PTB	-0,32	-0,14	0,00	0,11	0,16	0,13	0,02	0,00	-0,02	-0,12	-0,09	0,09	-0,02
CFP	-0,13	0,04	0,17	0,15	0,15	0,11	-0,05	-0,05	0,11	-0,19	0,21	0,10	0,01
DY	-0,04	-0,03	-0,05	0,14	0,23	0,26	0,03	0,07	-0,04	-0,31	-0,06	0,43	0,01
EY	0,01	0,09	0,14	0,42	0,45	0,45	0,26	0,31	0,74	-0,55	0,08	0,43	0,16
SP	-0,03	0,10	0,19	0,41	0,43	0,37	0,33	0,39	0,71	-0,59	0,11	0,58	-0,28
EBP	0,10	0,03	0,09	0,33	0,31	0,40	0,20	0,21	0,56	-0,41	0,07	0,24	0,38
S6	0,09	0,08	0,03	-0,14	-0,39	-0,24	-0,23	-0,26	-0,21	0,19	-0,08	-0,36	0,45
S12	0,05	0,02	0,03	-0,10	-0,33	-0,19	-0,21	-0,23	-0,12	0,19	0,06	-0,41	0,59
S24	0,09	0,06	0,05	-0,10	-0,29	-0,09	-0,17	-0,19	-0,03	0,09	0,06	-0,39	0,72
E6	0,07	0,09	0,07	0,20	0,11	0,12	0,15	0,17	0,44	-0,33	0,07	0,20	0,29
E12	0,11	0,13	0,13	0,13	-0,11	0,05	0,08	0,07	0,33	-0,14	0,03	0,04	0,34
E24	0,16	0,19	0,16	0,09	-0,09	0,05	0,07	0,05	0,30	-0,10	0,07	-0,08	0,48
D6	0,01	-0,02	-0,08	-0,30	-0,40	-0,36	-0,35	-0,39	-0,52	0,40	-0,12	-0,43	0,15
D12	-0,05	-0,16	-0,19	-0,24	-0,34	-0,27	-0,28	-0,31	-0,50	0,46	-0,06	-0,51	0,30
D24	-0,03	-0,06	-0,09	-0,14	-0,12	-0,12	-0,35	-0,38	-0,28	0,07	0,00	-0,39	0,66
DP12	-0,01	-0,13	-0,16	-0,26	-0,36	-0,29	-0,32	-0,33	-0,42	0,33	-0,04	-0,45	0,39
EP6	0,01	0,05	0,04	0,26	0,14	0,18	0,13	0,14	0,42	-0,33	0,06	0,13	0,45
EP12	0,17	0,06	0,06	0,24	0,10	0,14	0,06	0,08	0,42	-0,29	0,01	0,09	0,46
EP24	0,11	0,12	0,14	0,24	0,17	0,23	0,08	0,09	0,53	-0,34	0,10	0,11	0,46
PR	-0,03	-0,06	-0,10	-0,26	-0,25	-0,20	-0,39	-0,40	-0,72	0,18	-0,12	-0,11	0,07
ROE	0,03	-0,12	-0,17	-0,30	-0,45	-0,32	-0,16	-0,20	-0,52	0,62	-0,06	-0,53	0,31
ROA	-0,01	-0,15	-0,23	-0,24	-0,38	-0,26	-0,09	-0,13	-0,40	0,57	-0,17	-0,46	0,29
STA	0,04	-0,21	-0,24	0,21	0,29	0,18	0,32	0,33	0,35	-0,17	-0,06	0,36	-0,42
DC	0,19	0,02	0,05	0,03	0,13	0,07	-0,25	-0,22	0,29	-0,35	0,03	-0,09	0,42
OM	0,15	-0,08	-0,13	-0,32	-0,40	-0,26	-0,40	-0,45	-0,54	0,48	-0,10	-0,57	0,52
CXS	-0,02	0,16	0,08	-0,15	-0,29	-0,20	-0,21	-0,24	-0,39	0,28	0,01	-0,35	0,32
MOM1	0,00	0,14	0,12	-0,10	-0,06	0,01	-0,24	-0,24	-0,24	-0,01	0,00	-0,02	0,09
MOM3	-0,01	0,07	-0,02	-0,29	-0,29	-0,23	-0,38	-0,42	-0,47	0,21	-0,12	-0,28	0,14
MOM6	-0,03	-0,01	-0,10	-0,38	-0,38	-0,33	-0,38	-0,42	-0,52	0,34	-0,19	-0,40	0,19
MOM12	-0,12	-0,13	-0,17	-0,39	-0,37	-0,39	-0,32	-0,37	-0,53	0,43	-0,07	-0,44	0,23
MOM24	0,01	-0,09	-0,10	-0,40	-0,45	-0,40	-0,38	-0,43	-0,53	0,40	-0,06	-0,56	0,42
LNP	1,00	0,38	0,32	-0,06	-0,09	-0,03	-0,09	-0,09	-0,02	-0,01	-0,10	0,01	0,11
LNMV	0,38	1,00	0,91	-0,12	-0,09	-0,04	0,07	0,08	0,12	-0,09	0,09	0,09	0,05
LNEV	0,32	0,91	1,00	-0,11	-0,08	-0,03	0,03	0,05	0,15	-0,13	0,26	0,08	0,06
TVO6	-0,06	-0,12	-0,11	1,00	0,67	0,65	0,33	0,38	0,44	-0,32	0,04	0,47	-0,12
TVO12	-0,09	-0,09	-0,08	0,67	1,00	0,67	0,21	0,25	0,50	-0,47	0,02	0,50	-0,08
TVO24	-0,03	-0,04	-0,03	0,65	0,67	1,00	0,31	0,35	0,43	-0,38	0,02	0,41	0,00
STD	-0,09	0,07	0,03	0,33	0,21	0,31	1,00	0,98	0,55	0,03	-0,02	0,31	-0,37
VOL	-0,09	0,08	0,05	0,38	0,25	0,35	0,98	1,00	0,58	-0,03	0,01	0,36	-0,39
BET	-0,02	0,12	0,15	0,44	0,50	0,43	0,55	0,58	1,00	-0,50	0,05	0,41	-0,04
ITBT	-0,01	-0,09	-0,13	-0,32	-0,47	-0,38	0,03	-0,03	-0,50	1,00	-0,05	-0,60	-0,22
DE	-0,10	0,09	0,26	0,04	0,02	0,02	-0,02	0,01	0,05	-0,05	1,00	0,09	-0,02
DA	0,01	0,09	0,08	0,47	0,50	0,41	0,31	0,36	0,41	-0,60	0,09	1,00	-0,34
EM	0,11	0,05	0,06	-0,12	-0,08	0,00	-0,37	-0,39	-0,04	-0,22	-0,02	-0,34	1,00