Momentum Investing

The Multi-Asset Evidence

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Executive Summary

The tendency of investments to exhibit persistence in their relative performance was initially postulated by Jegadeesh and Titman in their 1993 Journal of Finance article. They postulated that investments, which had performed relatively well would continue to perform relatively well. Those investments that have performed relatively bad would continue to perform relatively bad. They named such a tendency momentum.

According to modern finance such a tendency cannot persistently be observed and exploited as any market anomaly would be eroded by the ubiquitous market efficiency. Given that the markets are fully efficient, investors should not expect arbitrage strategies as momentum to be profitable neither in the short nor in the long run. Any excess return relative to the market would not be feasible.

However, consecutive publications, following the 1993 article, have proven that momentum is more than a tendency. Long-short strategies in particularly equities and subsequently bonds, commodities and currencies have proven to be highly profitable due to underlying momentum dynamics. In consequence of such strategies, this thesis will illustrate that a parallel multi-asset momentum exists and that investors are able to exploit this using a cross-sectional multi-asset data sample. Adjusting the conventional momentum methodology, using a 12-year sample period and data sample of 50 indices, this thesis will illustrate that investors are able to invest in multi-asset portfolios based on the asset classes past relative performance. Shorting the past years worst performing assets to fund long positions in the past years best performing assets, and holding such trading portfolio for subsequently three months, investors would earn a significant excess return of 9.19 percent.

Additionally, this thesis will illustrate how positive market movements of equities and commodities as well as perception of low volatility tend to accelerate the multi-asset momentum. It will further illustrate how the multi-asset momentum is driven by the worst performing asset classes and illustrate how bull markets will accelerate the multi-asset momentum and how bear markets would erode multi-asset momentum, respectively.

Finally, this thesis will illustrate that capital markets should not to be perceived as fully efficient, hence investors should expect a plausible excess return to the market. Momentum should no longer be perceived as a random market anomaly, but rather as a ruling market factor.

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Chapter 1

Introduction

The old saying, *"prediction is difficult, especially about the future"*, symbolises the main motivation of this thesis. We extend the remark to the investment industry and ask: *"can investors make liable predictions of the future or is the future too diverse to be predictable"*? Answering such a question is obviously difficult and is strongly emphasised by the significant broad publication body of capital market predictability. To professionals, as well as private investors, predicting, and eventually exploiting, the future states of the capital markets have always been an quintessential task. The answer to such question is therefore not a binary *yes or no*, but rather, and perhaps more importantly, a varied question of *how*. Especially, if investors seek to exploit the predictability across markets. The question of *how* to potentially exploit the market predictability within as well as across capital markets will be the main scope of the thesis.

The contents of chapter 1 is divided such that section 1.1 will elaborate on the motivation for writing this thesis. Section 1.2 will concretise the motivation into a overriding thesis statement, followed by four research questions. Section 1.3 will limit the scope of the thesis and is followed by the applied methodology in section 1.4. Section 1.5 will link the subsequent chapters and sections in an guiding thesis structure.

1.1 Motivation

Inefficient Markets The main motivation for writing this thesis, originates from the fact that some investors, contrary to the efficient line of thinking, are able to produce methodical and significant excess return within distinct capital markets. This is contrary to the theoretical postulate that capital markets, at any point in time, will price in new asset-specific information fully efficient, so that any arbitrage potentials will be diluted. This way, observing investors producing excess returns should not be a feasible scenario. Despite this facts, excess return are frequently observed within several mutual and especially hedge funds, why capital market inefficiency has been of key interest to investment professionals. This thesis is motivated by these facts and will seek to determine *how* investors are able to exploit the inefficient environment within and across capital markets. The point of origin will be the trendseeking predictability of asset prices, which is commonly known as *momentum*.

Multi-Asset Momentum Due to the potential trend in asset prices, this thesis is moreover motivated by the 1993 Jegadeesh and Titman article (Jegadeesh & Titman, 1993), which established the methodology and evidence for actively exploiting price momentum within a US equity data sample. By basically applying a long-short strategy, Jegadeesh and Titman illustrated that investors were able to produce significant alpha utilising the trend in past equity prices. Today, the 1993 article embodies the origin of momentum investing and has subsequently been broaden to more diverse data samples. Thus, since 1993, consecutive articles on momentum in various asset classes have emerged, in addition to the well-established equity evidence. The evidential literature of the momentum profitability, within a wide range of broad asset classes, has motivated the multi-asset approach conducted in this thesis. As the momentum existence has proven to be significant *within* several asset classes, we will extend this knowledge, to test whether momentum is cross-sectionally significant *across* several asset classes. We will denote such strategy a *multi-asset momentum* strategy.

To summarise the thesis motivation, we believe that by studying the current financial theory as well as the current published body of momentum existence, we will be able to vindicate our main assumption that the capital market *are not* fully efficient. We believe that investors are able to utilise such knowledge to construct investment schemes that exploit the trend in past asset prices and generate significant and consistent alpha both within an asset class as well as across asset classes.

1.2 Thesis Statement

We will, in this section, concretise our motivation, which should enable a more tangible and explicit thesis statement. This is basically done by elaborating on the last paragraph of section 1.1. Our main hypothesis can be limited to the fact that we believe investors are able to construct investment schemes, which produce significant excess returns. We will claim that investors with a trendfollowing bias, will significant and consistent, be able to produce alpha utilising the applied methodology of thesis presents, both within asset classes as well as across asset classes. We will separate this thesis from former published articles, by adopting a multi-asset approach that enable portfolio positions from 50 asset class indices. The main thesis statement can be limited to the question of:

- *How investors compose investable multi-asset portfolios that significantly exploit the underlying momentum dynamics of four broad asset classes?*

As the thesis statement stated, we will study a market anomaly called momentum. We define *momentum* as a tendency of assets to exhibit persistence in their relative strength performance. Asset that have performed relatively well will continue to perform relatively well. Assets that have performed relatively bad will continue to perform relatively bad. We will extend this definition to several asset classes hence the *multi-asset* statement. Furthermore, the multi-asset positioning will be cross-sectionally performed, which allow investors to consistently to take positions in any of the applied asset classes. To support the thesis statement, we have established four research questions to ensure a common thread in the thesis.

- *Is the multi-asset momentum significant and profitable on a 12 month basis?*
- *Do certain factors significantly tend to drive the multi-asset momentum?*
- *Do certain time periods significantly tend to drive the multi-asset momentum?*
- *Which underlying asset classes tend to drive the multi-asset momentum?*

The research questions are embodied in the subsequent chapters as follows. Chapter 2 will ensure the theoretical basis of capital market investing as well as illustrate the theoretical basis behind the efficient market hypothesis. Chapter 3 will emphasise the basis of the equity momentum as well as present the current published momentum literature within four broad asset classes. This implicitly set the stage for the cross-sectional multi-asset momentum strategy. Chapter 4 presents inclusion criteria's of the applied asset classes as well as the robustness of the evidence in chapter 5. Finally, chapter 5 will elaborate on the applied methodology, the significance of the multi-asset momentum as well as illustrate a common explanations for the anomaly using factor models.

The four broad asset classes applied in this thesis will be equities, debt, commodities and currency.

1.3 Thesis Demarcation

To limit the scope of the thesis, we find it necessary to outline deliberate limitations to the thesis contents. These limitations are both composed of theoretical limitations, as well as practical limitations, and are predominantly intended to ensure valid and reliable thesis evidence. We initially limit our investable universe to the four broad asset classes; equity, debt, commodities and currency. This limitation is based on their inclusion in previous momentum literature as well as their mutual correlation structure. Furthermore, based on the four broad asset classes, we divide the latter asset classes in 50 sub asset classes, to ensure variety in our data sample. The 50 sub asset classes are selected to ensures a global investable multi-asset universe, with regard to traditional biases, ratings and regions. To limit the scope of the data sampling, we will apply indices from investment banks, with a wide industry acceptance. Six of the total 50 sub asset classes have been personally constructed following a fundamental indexation methodology.

We will furthermore limit our literature review to the four broad asset classes and as such only include the most significant published articles. As the momentum research was initiated in the equity segment, the literature review is heavily allocated towards this universe. We acknowledge that the literature review is not complete, yet find it representative in order to support the multi-asset momentum potential. We will further limit our econometric analysis to five common assumptions grounding financial time series. As we seek evidence of the strength and significance of the applied momentum portfolios, we find such common assumptions important to include. We acknowledge that the econometric analysis is not complete, as many further assumptions and hypothesis's could have been added, yet we assume that testing the five prerequisites, will be sufficient to support the empirical findings of the multi-asset momentum.

We will, in addition to the time series testing, limit the applied methodology to the 1993 Jegadeesh and Titman article (Jegadeesh & Titman, 1993). As the article has been the prevailing applied methodology in current momentum literature, we are confident that the multi-asset evidence, will not be biased by any methodological flaws. Finally, we intentionally do not allocate much space to the behavioural finance aspect, even though we acknowledge that momentum potentially could be driven by such theories. We will limit the behavioural part of the thesis to include the significant prospect theory as well as underline the basis of underreaction by inefficient investors. We are aware of the importance of the behavioural finance contribution to the momentum literature, yet we limit the scope of the thesis to construct and explain the significance of multi-asset momentum and leave the underlying behavioural explanation to future master's theses.

1.4 Thesis Methodology

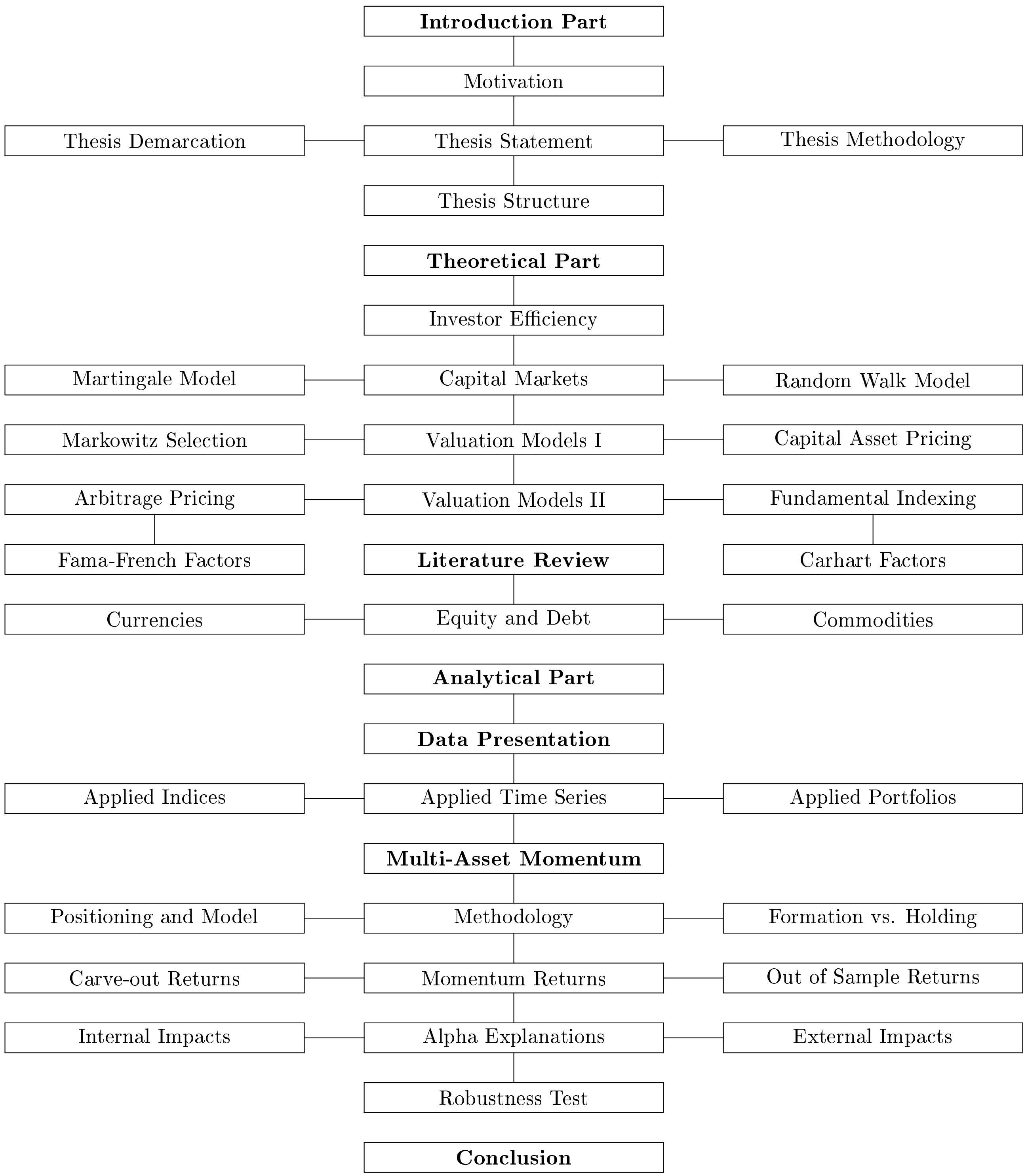
The applied methodology for the momentum model will tend to replicate the 1993 Jegadeesh and Titman article. We will elaborate on the article in chapter 5, as it seems more appropriate for the thesis. Briefly explained, the methodology allow investors to construct 25 combinations of momentum trading portfolios with long positions in the past best performing equities funded by short positions in past worst performing equities. The equities are ranked in deciles and the formation periods, as well as the holding periods, are based on previous 3 to 12 month periods. Each holding period is followed by a new formation period, etc. Combining such long-short investment strategies is commonly named a zero-cost trading strategy, as the long positions theoretically are financed by the short positions. The individual trading strategies in this thesis are based on positions in investment bank offered indices as opposed to conventional momentum literature that applies either single securities or futures. We do not construct the time series ourselves, as this is considered to be beyond the scope of the thesis. As the 1993 methodology initially was applied to an equity data sample, we are able to apply the same cross-sectional methodology to bonds, commodities and currencies. To ensure liquidity and practicability of the applied indices, we assume that positions in a distinct index can be taken through exchange traded funds, capturing the diversification of the investment universe without enduring the transaction costs from actually buying it.

The deductive part of the thesis will mainly be chapter 1, chapter 2 and chapter 3. They are intended to systematically produce an objective non-biased submission of the key theoretical foundation of the thesis and to emphasise the current level of comprehension and application from previous academic literature.

The inductive part of the thesis will be chapter 4 and chapter 5. They are intended to produce a subjective hands-on approach based on empirical observations that will work to potentially change the theoretical framework in order to make a generalised conclusion of the thesis statement.

The published articles mentioned in chapter 3 all consist of primary literature (except the 2010 Jovesta et. al SSRN working paper) as well as the remainder of cited academic books and journals. This is a deliberate decision as biased literature could potentially interfere with the thesis methodology. The primary literature is included and cited if the publications appeared in credible and industry specific journals that serve as cutting-edge academic publication bodies. The cited secondary literature is limited to Thomas Reuters Datastream, Bloomberg and SAS 9.2.

1.5 Thesis Structure



Chapter 2

Foundation of Investment Management

Before turning to the literature review in chapter 3, and the core analysis in chapter 5, we consider it necessary to present the basis of the financial theory we relate to throughout the thesis. This chapter is not intended to serve as an exhaustive presentation of the modern financial theory, yet it will present the theoretical implications for investors seeking to exploit anomalies in capital markets. It will briefly illustrate the behavioural biases of professional, as well as private investors, and explain how we define efficient markets. It will furthermore illustrate, how we theoretically price assets and how we evaluate a risk-return relationship. It furthermore present, how we are able to enhance the expected return without altering the investment universe by constructing fundamental indices, as opposed to the traditional market weighted indices. Additionally, it illustrates how we can use factor models to gain a deeper insight into the origins of alpha creation. The various sections in chapter 2 will both explicitly and implicitly be applied in chapter 5.

The contents of chapter 2 is divided such that section 2.1 and section 2.2 illustrates how we define rational investor behaviour and why theoretical investor behaviour often cannot be observed empirically. Section 2.3 illustrates how we define an efficient market as well as the randomness of asset prices. Section 2.4 illustrates how we price assets and how we are able to compose fundamental indices from a given benchmark universe. Finally, the last section 2.5 illustrates we use factor model to estimate the true alpha contribution.

2.1 The Efficient Investor

Investor Rationality

The overriding assumption of the dynamics of asset pricing is that all investors are behaving rationally and are assumed to maximise their individual expected utility using a complete set of static preferences from an aggregated level of information solely motivated by self-seeking interests (Marekwica, 2011).

Theoretically speaking, investors are divided in two contradictory groups: the risk seeking investors and the risk averse investors (Bodie et al., 2009). The risk-seeking investors will have a convex utility function as an increase in the overall risk will result in a higher expected utility of the investment, thus a higher profit to the investors. On the contrary, risk averse investors will have concave utility functions as the risk averse investors would rather settle with a lower gain rather than taking on more risk (Marekwica, 2011). This effect symbolises the expected utility theory. Despite the fact that the rational investors are maximising his or her expected utility, investors are generally considered to be risk averse. An important point is that all investors are exposed to the same level of information such that no investor is given preferential treatment (given that inside information in not available).

The rationality and self seeking behaviour implies that investors are evaluating a simple risk-return trade-off, assigning a given utility level to each outcome based on the individual risk aversion (Bodie et al., 2009). The rationality is furthermore linked to the competitive environment of the market participants, symbolised in the *survival of the fittest* statement. Investors need to outperform the market, i.e. the other investors, to survive, which is also the overriding assumption of the random walk hypothesis in section 2.3. Any market pricing error would this way consistently be eliminated by the competitive actions of the market participant.

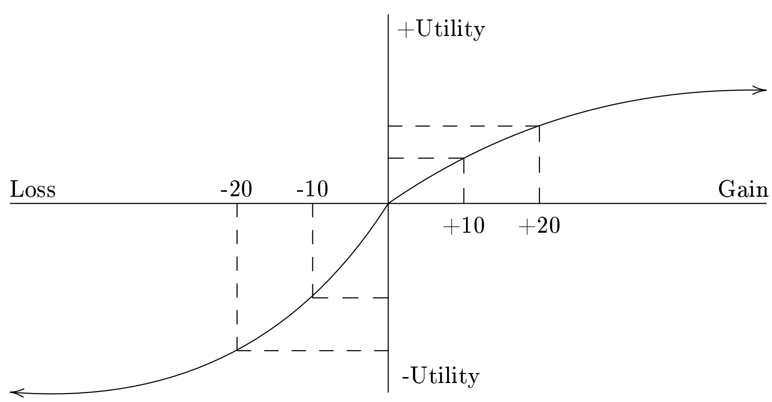
However, as this thesis will exhibit, the market randomness and rationality of the investors is not as explicit as the theory prescribes.

2.2 Investor Behaviour

In 1979, Daniel Kahneman and Amos Tversky (Kahneman & Tversky, 1979) published an article on actual investor behaviour as opposed to the rational expected utility theory. Their theory was named the *prospect theory* and described the various mental states of investors that potentially could have significant impact on the rationality, i.e. decision making, of the investors. The article illustrated a *certainty effect* relating to the strong preference by the investors for a certain outcome instead of an uncertain. This way, Investors evidently would rather select a certain outcome than committing to a gamble, despite the fact that the final value of both outcomes would be the same. For example, the investors should be indifferent between an certain gain of 10 and a gamble that either results in a gain 100 with 10 per cent probability or nothing with 90 per cent probability. The expected gain would in either cases be 10. Furthermore, the article illustrated a *loss aversion* which related to the fact that a given loss has a higher negative impact on the expected utility over and above the corresponding gain. This implied that investors are risk averse, however only to the extend that they are experiencing investment gains. Given that investors are incurring investment losses they will tend to be more risk seeking. Those actions are reflected in the *reflection effect* that is furthermore illustrated in the article. This way, the actual investors behaviour is not as symmetric as the rationality theory prescribes. Investors actually base their actions on relative changes in wealth rather than the absolute change. Figure 2.1 illustrates the *certainty effect* and the *reflection effect*.

Figure 2.1: **Prospect Theory**

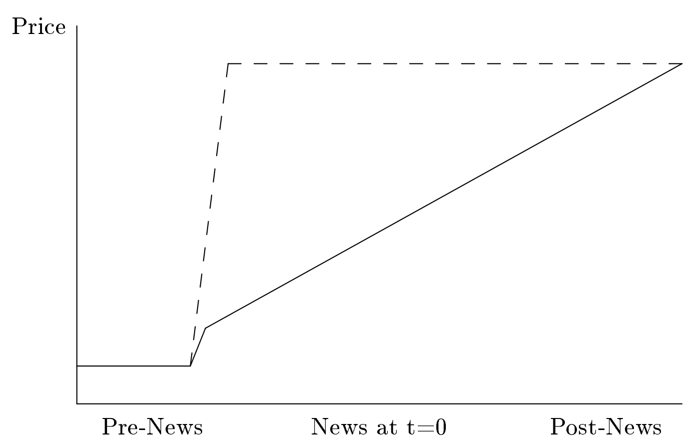
Figure 2.1[1] illustrates the *prospect theory*. Investors do not have symmetric value functions due to behavioural biases such as the *certainty effect* as well as the *reflection effect*.



As figure 2.1 illustrates, investors are more affected by losses, than the corresponding gain. In 2006, Andrea Frazzini (Frazzini, 2006), extended the knowledge of the prospect theory and added a *disposition effect* that previously was illustrated in the financial literature (Shefrin & Statman, 1985). He showed, that emergence of new asset specific information would be incorporated differently by investors causing behavioural biases in the current asset prices. The origin to these biases should be found in the *reflection effect* and the *disposition effect*. The *reflection effect* was the tendency of risk seeking and risk averse investment behaviour (Kahneman & Tversky, 1979) and the *disposition effect* was the tendency to hold on to losing assets too long and sell winning asset too early (Shefrin & Statman, 1985). Figure 2.2 and figure 2.3 illustrate these effects. In figure 2.2 an asset can basically either trade at a capital gain or at a capital loss. If an asset, trading at a capital loss, is experiencing positive news, investors will tend not to sell the asset to lock-in the positive news effect. They would rather maintain their positions in the asset. Such opportunistic and risk seeking behaviour follows from the *reflection effect*. The reluctance to sell the asset will cause an excess demand of the asset and the price would adjust rapidly to the fundamental value. This is illustrated by the dotted line.

Figure 2.2: **Underreaction to positive news**

Figure 2.2[2] illustrates the underreaction of investors given they encounter positive news in either an asset trading at a capital gain (—) or a capital loss (- -), respectively.

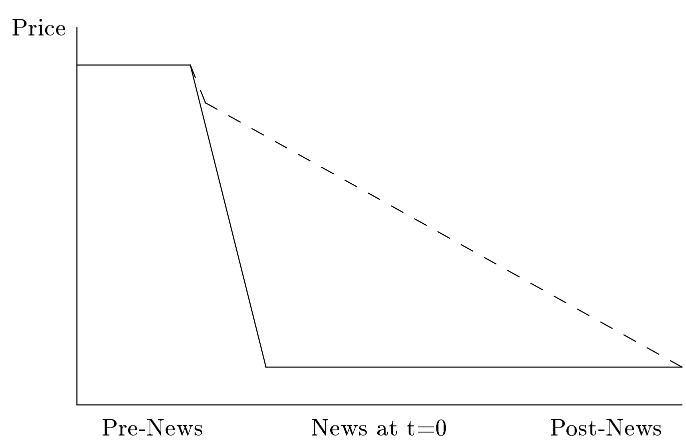


On the other hand, if the asset was trading at a capital gain, investors would sell the asset at once to lock-in the positive news effect. Such pessimistic and risk averse behaviour can furthermore be traced to the *reflection effect*. This rapid selling action would cause an excess supply of the asset, which would lead to a slow price impact. This is illustrated by the filled line. The example indicates, that good news travels slowly across assets trading at capital gains due to the underreaction by investors.

Such underreaction would potentially infer post-event drifts that increases the price predictability of asset prices (Frazzini, 2006). The example can furthermore be illustrated in case of negative news emergence. Figure 2.3 illustrates an asset trading either at a capital loss or at a capital gain. If such asset is currently trading at a capital loss, and experiencing additional negative news, investors would be reluctant to sell of the asset due to the *reflection effect*. This opportunistic and risk seeking behaviour would entail, that investors would rather continue to ride loses, than limit their current deficit. The reluctance to sell of the asset would create supply shortage hence the price adjustment will not be as rapid as expected. This is illustrated by the dotted line. On the other hand, given the asset is trading at a capital gain, investors would behave pessimistic and risk averse and lock-in the available profit by selling of the asset. This selling action would adjust the asset price to the fundamental price rapidly due to the excess supply. This is illustrated by the filled line. The example indicate that bad news travels slowly across asset trading at a capital loss which potentially infer, the same way as in case of positive news, post-event drifts, that increases the price predictability of asset prices (Frazzini, 2006).

Figure 2.3: **Underreaction to negative news**

Figure 2.3[3] illustrates the underreaction of investors given they encounter negative news in either an asset trading at a capital gain (—) or a capital loss (- -), respectively.



Section 2.2 illustrated, how investor behaviour implicitly created inefficiencies in the capital markets. Observing and exploiting such inefficiencies, as the post-event asset price drift, increases the potential of creating momentum strategies, that captures information in the ex post asset prices. We will exploit this knowledge in our momentum model in chapter 5. The next section 2.3 will broader the theoretical basis of the efficient market.

2.3 The Efficient Capital Markets

2.3.1 The Fair Game Model

The *efficient market hypothesis* is the underlying basis of modern financial theory and originates from investor's efficiency. The theory defines information in the capital market as being efficient, which entails asset prices fully reflect all available market information (Grinblatt & Titman, 2002). Given that asset trade at a well-organised capital market all investments would have *net present value* of zero (Ross et al., 2008). If prices are neither too low nor too high the difference between the market value and the intrinsic value is zero. Investors get what they pay for, so to speak. As equation 2.1 states, the expected future asset price given the current level of information, Φ, is equal to the compounded return of the asset

$$E(p_{i,t+1} \mid \Phi_t) = [1 + E(p_{i,t+1}) \mid \Phi_t] \cdot p_{i,t} \tag{2.1}$$

The efficient market hypothesis assumes that investing in the capital markets can be expressed as a *fair game* model following (Fama, 1970). Equation 2.2 shows that the current price does not rely on any past prices and the expected price divergence utilising past price information is equal to zero as stated in equation 2.3

$$E(p_{i,t+1} \mid p_{i,t-1}, p_{i,t-2}...) = p_{i,t} \tag{2.2}$$

$$E(p_{i,t+1} - p_t \mid p_{i,t-1}, p_{i,t-2}...) = 0 \tag{2.3}$$

Following equation 2.3 the expected value, x, exploiting the current available information, Φ, will be zero as stated in equation 2.5

$$x_{i,t+1} = p_{i,t+1} - E(p_{i,t+1} \mid \phi_t) \tag{2.4}$$

$$E(x_{i,t+1} \mid \phi_t) = 0 \tag{2.5}$$

Following equation 2.5 the future excess return, z, of an asset will be zero following equation 2.7

$$z_{i,t+1} = r_{i,t+1} - E(r_{i,t+1} \mid \phi_t) \tag{2.6}$$

$$E(z_{i,t+1} \mid \phi_t) = 0 \tag{2.7}$$

The fair game hypothesis states that if a game is fair, i.e. markets are truly efficient, then the future price should be expected to equal the current market price. If equation 2.3 and equation 2.5 holds true, then the actual asset prices will equal their rational prices and the market will truly be efficient. Due to the fair game model assumption, investors neither empirically nor theoretically are able to earn an abnormal return solely using market information as an explanatory variable, following equation 2.7. Asset prices are at any time priced according to their rational value given the available current market information. New market information is priced in simultaneously with the emergence of that information. This way, the investor's best alternative in maximising their expected utility, i.e. wealth, would be to chose the investment strategy that simply buy and hold an aggregated market portfolio. According to the efficient market hypothesis the capital markets can attain three stages given the characteristics of the available information (Bodie et al., 2009).

The first state of market efficiency is the *strong state*. Under the strong state of market efficiency, all available information, both currently available in the market as well as *inside information*, is contained in current asset prices. If investors believe that the capital markets are efficiently strong, then they do not expect to be able to consistently generate alpha in their portfolios and any excess performance is expected to be due to short term luck (Brealey et al., 2008; Fama, 1970). The likelihood of a strong efficient capital market is, however, very low, and to expect corporate insiders not to have access to any pertinent information that is not currently available in the market is difficult to imagine. The strong state of market efficiency therefore serves primarily as an extreme case. The second state of market efficiency is the *weak state*. Under the weak state of market efficiency, current asset prices follow a *random walk process* (Brealey et al., 2008; Fama, 1970). This way, past price information cannot be used as predictor of future asset prices. Information about past prices are publicly available and virtually costless to obtain. This implies that investors are not able to consistently generate an abnormal return using past information. If investors believe that the capital markets are efficiently weak, then they reject any form of macroeconomic cycles, momentum, reversals, style bias or size biases. Any predictable patterns in the capital markets do not exist, hence any application of technical analysis does not add value to investment decisions. The weak state of market efficiency serves, the same way as the strong state of market efficiency, primarily as an extreme case. To expect that capital markets are not biased from any of the above mentioned predictable patterns is difficult to imagine. The third state of market efficiency is the *semi-strong state*. Under the semi-strong state both past prices as well as all *public information* concerning the future prospects are priced in (Brealey et al., 2008; Fama, 1970). Investors cannot consistently earn an abnormal profit using solely idiosyncratic information nor analysing macroeconomic trends as such are already priced in the equities. This ensures that markets do not under- or overreact to new information. The semi-strong state is presumed to provide the most accurate picture of the true capital markets. It should be noticed however that an efficient market does not mean that investors are able to construct portfolios on the basis of throwing darts at the Financial Times. It simply means that investors should not expect to benefit from any new information to the market (Ross et al., 2008).

2.3.2 The Random Walk Model

The efficient market hypothesis, especially the weak state, is closely associated with the *random walk hypothesis* where the unimpeded stream of information is immediately priced in the asset prices. Current market prices are furthermore independent and uncorrelated to previous price patterns. The random walk hypothesis postulates that capital market have no memory, and at any time the actual market prices reflect the rational value of an asset (Campbell et al., 1996). Though the efficient market is practically not attainable, the random walk hypothesis relaxes the rational value assumption and allows the actual market price to wander randomly, i.e. the fair game model does not fully apply. Three basic definitions of the random walk hypothesis exists distinguished by their individual residual restrictions (Campbell et al., 1996), where the simplest version is the *random walk I.* In the random walk I, equation 2.8, not only are the residuals independent and identical distributed, but also any nonlinear functions of the residuals are independent. It follows that:

$$RWI^4: \qquad p_{i,t} = \mu + p_{i,t-1} + \epsilon_{i,t} \qquad \epsilon_{i,t} \sim IID \quad N(0, \sigma^2) \tag{2.8}$$

where, μ, is the expected drift-factor, ϵ, is the error terms and, IID$(0,\sigma^2)$, denotes that the ϵ's are independent, identical and normally distributed with a mean of zero and equal variance. The independent term denotes that the residuals are uncorrelated, and the term identical denotes that the residuals have a stable drift-factor such that market volatility is stable. In practice, the identical term is not achievable in the long run due to volatility clustering and the assumption is adjusted in the *random walk II* in equation 2.9. Under the premises of random walk II the assumption of independent distribution residuals is maintained, however residuals are no longer expected to be identically distributed.

$$RWII^4: \qquad p_{i,t} = \mu + p_{i,t-1} + \epsilon_{i,t} \qquad \epsilon_{i,t} \sim ID \quad N(0, \sigma^2) \tag{2.9}$$

Even though the random walk II is less restrictive than random walk I the most important application of the random walk hypothesis, the independence, is maintained to ensure that any arbitrary future price movement is unpredictable using past prices. In the *random walk III* from equation 2.10, the independence term is relaxed to include processes with dependent, but uncorrelated residuals. This means the random walk III allows for e.g. short term momentum in prices. A process with uncorrelated residuals that allows for correlated ϵ^2 is therefore not independent and thus satisfies the random walk III.

$$RWIII^4: \qquad cov(\epsilon_{i,t}, \epsilon_{i,t-k}) = 0 \quad \wedge \quad cov(\epsilon_{i,t}^2, \epsilon_{i,t-k}^2) \neq 0 \tag{2.10}$$

However, a finite conclusion of market efficiency can only roughly be tested. Due to the *joint hypothesis* problem, it is impossible to clarify if an inefficient market is truly inefficient or biased from an incorrect equilibrium model (Campbell et al., 1996).

2.4 Asset Valuation Models I: Markets in Equilibrium

2.4.1 The Markowitz Portfolio Selection Model

Once familiar with the underlying behavioural biases of the investors as well as the definition of the capital market efficiency we present the underlying science of asset pricing. One of the most influential articles in modern finance is the 1952 article by Harry Markowitz (Markowitz, 1952). Markowitz assumed that investors would compose their individual portfolios based solely on a *mean-variance analysis*, i.e. only optimise the relationship between expected return (mean) and the associated risk (standard deviation). The mean-variance analysis is based on the assumption, that capital markets are frictionless, and that the portfolio return can be expressed as equation 2.11, given the specific asset weights, w_i, and returns, μ_i, and the total number of assets, n,

$$\mu_p = \sum_{t=1}^{n} w_i \mu_i \tag{2.11}$$

and the portfolio risk can be expressed as equation 2.12, given the individual asset risk, σ_i, and the covariance between an asset i and asset j, $cov_{i,j} = \sigma_i, \sigma_j \rho_{i,j}$

$$\sigma_p^2 = \sum_{t=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j \rho_{i,j} = \sum_{t=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_i w_j cov_{i,j} \tag{2.12}$$

The mean-variance analysis allowed any informed investor to rationally optimise his or her portfolio, given the set of asset returns and associated risk (Marekwica, 2011). Managing the mean-variance relationship assist the investors towards the optimal asset diversification, following equation 2.13,

$$E(r_{i,t}) - r_{f,t} = \sigma_i \frac{E(r_{M,t}) - r_{f,t}}{\sigma_M} \tag{2.13}$$

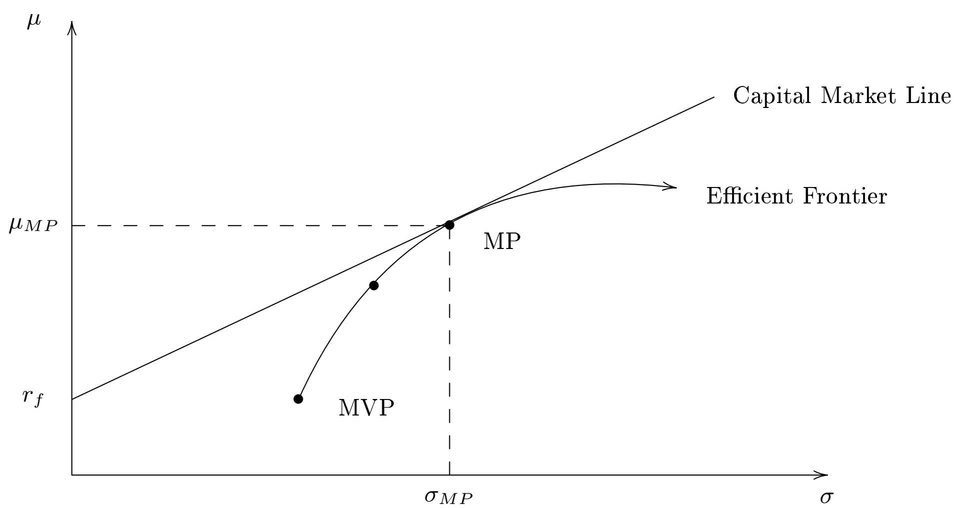
where, $E(r_i)$, is the expected return of an asset or portfolio, r_f, is the return of a risk-free asset, $E(r_M)$, is the expected return of the market portfolio and, σ, is the variance of a given asset or market. In a simple one period model, the least risky mean-variance portfolio is called the *minimum-variance portfolio*. Though minimising the overall portfolio variance is an essential objective to investors, the optimal mean-variance portfolio is called the *tangency portfolio*, which also can be referred to as the *market portfolio*. According to theory, investors are assumed to be optimising their individual portfolios towards this portfolio. The optimal risk-adjusted return is called the *sharpe ratio* (Marekwica, 2011) and is expressed in equation 2.14 as the *price of risk*:

$$r_{sharpe} = \frac{r_i - r_f}{\sigma_i} \tag{2.14}$$

where r_i is the return of a given asset or portfolio, r_f is the return of a risk-free asset and σ is the variance of a given asset or portfolio. The sharpe ratio as well as the mean-variance relationship is the basis of asset performance measures, and as a result will be used in subsequent sections. The mean-variance approach can furthermore be seen from figure 2.4. The figure illustrates the Markowitz portfolio selection model as consisting of an infinite number of feasible mean-variance portfolios located on and underneath the *efficient frontier* touching the *capital market line*. The efficient frontier represents the linkage between the fixed risk-free rate of return and the return of the market portfolio. All portfolios located on the efficient frontier are called efficient dominating portfolios (Marekwica, 2011) . This is the place investors adjusts their portfolios towards, since it will produce the highest expected return at a given level of risk.

Figure 2.4: **Mean-Variance Relationship**

Figure 2.4[5] illustrates the *minimum variance portfolio* as well as the *market portfolio*, both part of the *efficient frontier*. The *capital market line* is plotted as the tangent to the market portfolio and represent the relationship between the risk-free return and the market portfolio.



Any portfolio on the efficient frontier can be constructed by a weighted-average of any two portfolios located on the efficient frontier. This manoeuvre is named the *two-fund separation theorem* (Merton, 1972). Given that investors, at any point in time, will rationally optimise their portfolios towards the efficient frontier, no investor would be able to outperform the market. While the standard deviation is a measure of *total risk*, investors are prone to identify the *market risk* of their investments, which is introduces in the next section.

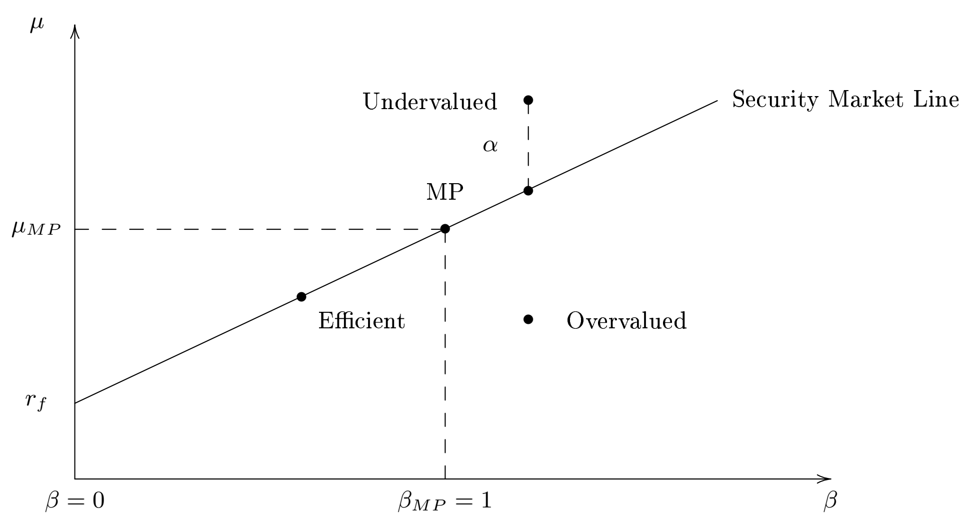
2.4.2 The Capital Asset Pricing Model

The *capital asset pricing model* emerges from the foundation of the Markowitz mean-variance analysis and is one of the most applied asset pricing models in the investment industry. The model incorporates the assumption of a frictionless capital market and is based on a number of extreme restrictions and was introduced in the 1964 article by William Sharpe (Sharpe, 1964). Given that the market portfolio represents all feasible assets available in the economy, the model postulates that the market risk must be equal to one and was symbolised by the beta measure. If portfolios or assets have higher (lower) betas than the market portfolio it follows that they will have a higher (lower) market risk than the market. This way, asset above the efficient market line will be undervalued and investors should expected to earn an abnormal return i.e. alpha. This is illustrated in figure 2.5. The security market line represents the linkage between the fixed risk-free rate of return and the market portfolio, thus expressed using equation 2.15, where β is the market risk.

$$E(r_{i,}) - r_{f,t} = \beta_i(E(r_{M,t}) - r_{f,t}) \tag{2.15}$$

Figure 2.5: **Mean-Beta Relationship**

Figure 2.5[6] illustrates the feasible set of *efficient portfolios* along the *security market line* including the *market portfolio*. This line represents the relationship between the *market risk* β and the risk-free rate.



Though the model is inevitable within every area of investment decision it has, along with the efficient market hypothesis and the random walk hypothesis, several weaknesses in relation to empirical tests. This originates from the extreme assumptions underlying the model. These are, that investors are many, with endowments too small to move the overall market, and expected to be price takers due to perfect market competition. Furthermore investors are myopic and every investor invests for one identical holding period. Investors have homogeneous expectations and are rational mean-variance optimisers. The investment universe is limited to publicly traded financial assets and investors are able to leverage their investments using a fixed risk-free rate. There are neither taxes nor transactions costs (Marekwica, 2011). Due to these assumptions, the capital asset pricing model, along with the efficient market hypothesis and the random walk hypothesis, represents merely guidelines rather than empiric observed evidence.

2.4.3 Fundamental Indexation

Extending the capital asset pricing approach, thus making the market portfolio more varied, we utilise the foundation of fundamental indexation (Arnott et al., 2005). Six of the 50 time series from the data sample are based on this approach, why we allocate space for the most crucial parts of the index composition. As illustrated by preceding sections, the capital asset pricing model is the theoretical basis of capital market investments despite the fact that it possesses several weaknesses. According to equation 2.5, equation 2.7 and the random market assumption from equation 2.8, investors should not be able to significantly outperform the aggregated market as long as they are limited to this exact universe. However, evidence has shown that especially value managers have been able to outperform a distinct benchmark. One reason lies in the market weighted approach of the investment banks, where a broad market is divided in value and growth, respectively, using a 50/50 approach. This way, 50 percent is assumed to be value and 50 percent is assumed to be growth (Arnott et al., 2005). Despite the fact that investors are able to invest more actively using passive value or growth indices, we find the methodology inefficient in the case of the 50/50 approach. Ceteris paribus, the 50/50 approach eventually will entail that the indices would include value and growth equities that is not purely value or growth. Contrarian investing with Morgan Stanley, Russell, S&P etc. produces such biases for the investors.

Due to these biases, the methodology of the fundamental indices only include the pure definitions of the contrarian assets enabling more accurate investment universes. We use five multiples as value and growth determinants, respectively. Thus, it has to be noticed that such determinants vary across strategies. In this case, high multiples indicate value while low multiples indicate growth. We chose the multiples *Book-to-Price*, *Earnings-to-Price*, *Dividend-Yield*, *Quick Ratio* and *Equity-to-Debt*

The *price-to-book*, as well as the *price-to-earning* multiples illustrate the price investors have to pay for either one unit of book value or earnings, respectively. The *dividend yield* illustrate the annual dividend payment per share and the *quick ratio* illustrate the short run liquidity i.e. current assets relative to current liabilities. The last multiple is the overall *leverage* of the company i.e. total equity relative to total debt. Value investors will optimise towards buying underpriced companies with low price multiples as well as companies with high dividend yields. This way investors will not be contributing to the growth of the company. Furthermore, value investors seek to buy the most liquid companies, thus avoiding growth drivers as liabilities. This way, value investors would moreover seek to buy companies with low leverage, i.e. high equity. One way investors may benefit from the mispriced assets in a given market is by longing or shorting such asset in the market hence such strategy is named a long-short strategy. If the price on an asset is too high relative to its expected market value, investors should short the asset and invest the cash inflow. As the prices diverges towards the consensus price i.e. a lower price, investors should buy back the asset and sell his or her investment. This way the total return would yield a spread equal to the arbitrage trading.

We screen the entire global equity universe with respect to the five multiples and remove the 2.5 percentile in the upper and lower part of the sample. We standardise the multiples using a traditional z-score following equation 7.5. Significant high (low) z-scores indicated strong value (growth) characteristics in the five multiples, respectively. We form an equally weighted characteristics-score based on equation 7.7 and the five z-scores. Only companies with a $value_{z-score} > 0 \mid growth_{z-score} < 0$ is regarded to be pure value (growth is the inverse following equation 7.8). The fundamental index only include pure value in a value universe. Investors have the opportunity to construct a $\frac{-n}{x}$ hyperbola, to specify the strength of a given characteristic from one to five. Plotting the value z-score on the 2^{nd} axis and the growth z-score on the 1^{st} axis, given a strength of two we can in the 2^{nd} quadrant exclude companies with biased characteristic if they lie to far to the left on the hyperbola.

Using the methodology outlined above allow investors to better exploit the true value or growth potentials in the market, which furthermore has the potential of exploiting more accurate arbitrage in the market. Performance-wise the top part of figure 7.1 indicates that superior performance can be inferred by a fundamental approach. The next section will illustrate how excess returns, despite the assumption of an efficient capital market, can be significantly explained by common risk factors in the market such as beta risk, size, style or momentum.

2.5 Asset Valuation Models II: Risk-adjusted Models

2.5.1 The Arbitrage Pricing Model

One of the earliest factor pricing theories was the *arbitrage pricing theory* (Ross, 1976), that contrary to the numerous restrictions of the capital asset pricing model, solely relied on the sensitivity to a common market factor. The theory assumes that there are sufficient assets in the investment universe to fully diversify from idiosyncratic risk, i.e. perfect competition, and that arbitrage opportunities are not viable (Bodie et al., 2009). Given the *factor loading F*, of a given factor, the arbitrage pricing theory can be expressed as the relationship between a risky asset, r_i, the related systematic factor load, $\beta_{i,n}$, an idiosyncratic component, ϵ, as well as an excess return, α_i illustrated in equation 2.16

$$r_i = \alpha_i + \beta_{i,1}F_1 + ... + \beta_{i,n}F_n + \epsilon \tag{2.16}$$

This way, the arbitrage pricing theory states that if asset prices follow a given factor structure, the expected return will follow the sensitivities to such factor. This can furthermore be expressed subtracting a risk-free rate r_f in equation 2.17

$$E(r_i) - r_f = \beta_{i,1}RP_1 + ... + \beta_{i,n}RP_n \tag{2.17}$$

Given that β_n loadings are zero, the expected risk premium would be zero following equation 2.7 and equation 2.17. This means that the *risk premium RP*, of any given factor can be set as explanatory variable to the expected return of a given security. Often factors are related to macro economic risks such as *inflation, GDP, yield curves* etc. Recent evidence has shown that *"investing in indices has several potential arbitrage trading benefits as most indices are reported at a low frequency that often involving significant estimation errors"* (Wind, 2012). This knowledge will be crucial to the next sections that introduces direct ways of exploiting the endeavours of the arbitrage pricing theory using asset specific risks such as market, size, style and momentum. Even though the arbitrage pricing theory is more realistic compared to capital asset pricing model, the arbitrage pricing theory still leaves several risk measures unanswered. The next section introduces an additional two factors to the market factors, which evidently have proven to significantly drive asset prices.

2.5.2 The Fama-French Three-Factor Model

The arbitrage pricing theory introduces the potential of exploiting arbitrage, i.e. inefficiencies in the market, to earn a spread between the inefficient price and the consensus price. The application of the *fama-french three-factor model* (Fama & French, 1996) extended this approach and gave an alternative and more direct approach describing the sources of systematic risk in asset returns. Fama and French postulated that a number of firm-specific characteristics could be located as explanatory variables in understanding and exploiting the potential inefficiencies in an given asset. Where the arbitrage pricing theory include an arbitrary number of factors, the Fama and French additionally includes the market capitalisation of an individual asset relative to a given investment universe (Small-Minus-Big), the book-to-market value of an individual company relative to a given investment universe (High-Minus-Low) as well as the market return. The expectation for the Fama and French was that the expected return of a given asset could be explained by three common risk factors illustrated by equation 2.18:

$$E(r_{i,t}) = \alpha + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \epsilon \tag{2.18}$$

where MKT is the market factor, SMB is the small firm effect and the HML is the value effect. The residual α is the part of the excess return that cannot be related to neither of the factors.

This first factor is called the size factor (henceforth SMB) as the factor is constructed shorting high capitalised equities and longing low capitalised equities, i.e. Small-Minus-Big. Empirically the underlying basis is that investment managers tend to overweight towards the small capitalised segment and outperform the aggregated market index (Marekwica, 2011). This can be justified by the actual excess performance of the small capitalised equities relative to the high capitalised equities. Given an overweight in the small capitalised segment, any alpha created by the investment manager would be explained by a positive significant sensitivity in relation to the Fama and French size factor.

The second factor is based on the underlying intrinsic value relative to the market value. This factor is called the style factor (henceforth HML) as the factor was constructed shorting growth equities and longing value equities, i.e. High-Minus-Low. The growth versus value is a practice investor seek in different market environments. Especially the US investor Warren Buffet allocate profitably towards a value bias in his portfolios. Rather than searching for superior growth opportunities, value investors tend to buy equity that exercise deep value in the books relative to its market value (Marekwica, 2011). Given that the market value of an equity is lower than its intrinsic value, value investors would buy the equity and hold it until the market value reaches an acceptable level. However, the value definition is not solely related to distinct multiples. Besides book-to market prices, investors often relate value to low growth rates, low price-to-earnings, high equity capital, which we applied in the fundamental methodology in section 2.4.3. This way value investing is counterintuitive according to the traditional assumption that growth is good. However, the support for value is overwhelming and historically value equities have significantly outperformed growth equities illustrated in top part of figure 7.1. This has been evident in the last two decades, however, it is worth noticing that value has had severe challenges during the last four years. Given an overweight in the value segment any alpha created by the investment manager would be explained by a positive and significant sensitivity in relation to the Fama and French style factor.

2.5.3 The Carhart Four-Factor Model

The fama-french three-factor model extended the theory from the arbitrage pricing theory by expanding the former by three distinct factors. Thus both models have the potential of illustrating the factor loading on any excess return. In the mid 1990 the style and size potential in assets was no longer sufficient to fully explain the abnormal return of asset managers. Markets were no longer assumed to be fully efficient and arbitrage across asset classes emerged. Academically, one of the most studied market anomalies was the momentum effect, which has been the focus of several articles. In 1997 the knowledge from the Fama and French model was extended by adding a momentum factor to the model (Carhart, 1997). The purpose of this factor was to capture the distinct momentum in assets due to the inefficient markets. Despite the alpha potential of momentum investing, such a strategy has not yet significantly proven to be a profitable long run investment strategy. Momentum investing is frequently profitable in the short term, especially on a 3 to 12-months basis as seen in chapter 3. The momentum factor was based on the 1993 Jegadeesh and Titman article (Jegadeesh & Titman, 1993), which constructed momentum time series based on the performance of the best and worst performing deciles in a given sample. Carhart located the loser and winners by constructing arbitrary formation and holding periods and captured momentum evidence by shorting the past worst performing assets and longing the best past performing assets, i.e. Up-Minus-Down (henceforth UMD). Carhart illustrated that by following such strategy investors could earn a significant momentum arbitrage in periods up to 12-months. Extending the Fama and French model by and addition momentum factor, the Carhart regression is illustrated in equation 2.19:

$$E(r_{i,t}) = \alpha + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \beta_{i,UMD}UMD + \epsilon \tag{2.19}$$

where MKT, SMB and HML is the three FFM factors and UMD is the momentum factor based on shorting and longing assets, respectively.

Chapter 3

Literature Review

The literature review in chapter 3 will underpin the significance as well as the evidence of previous published momentum articles within four broad asset classes. As equity momentum has been the point of interest for the majority of the included published articles we include six articles on US equity market momentum and four articles on European equity market momentum to the literature review. As the evidence is not as strong in the remaining three asset classes, we furthermore include two articles per asset class to limit the scope of the thesis. We are reviewing a total of 17 published articles of momentum in equity, debt, currency and commodities, respectively. One additional article is included to currencies, as the methodology is fundamentally different from the remaining 16 articles. We have chosen to focus on the data sample, the sample period, the research methodology as well as the ranking criteria and the combination of formation and holding periods. Finally, we report the alpha from the strategies in addition to the t-statistics.

The contents of chapter 3 is divided such that section 3.1 illustrates the US equity market evidence, which is primarily composed of the NYSE, NASDAQ and AMEX. Section 3.1 further illustrates the European market momentum within the largest European economies. Section 3.2 illustrates the currency momentum and section 3.3 illustrates the debt momentum. Finally, section 3.4 illustrates the commodity momentum across a sample of various commodities. We summarise the conclusions in section 3.5 as well as table 3.4.

3.1 Momentum in the Equity Markets

The US Evidence

Jegadeesh and Titman, 1993 As mentioned in the preface, several of the earliest equity momentum articles serve as the methodological body of the subsequent momentum studies both across as well as within asset classes. This methodological body originate from the 1993 Journal of Finance article by Narasimhan Jegadeesh and Sheridan Titman (Jegadeesh & Titman, 1993) and their empirical cross-sectional study of the momentum evidence in a distinct equity market. The 1993 article, as will later become evident, serves as the overriding guideline for portfolio formation as well as sub-sample analysis. The data sample covered a 25-year sample period from 1965 to 1989 and contained all listed equities on the NYSE and the AMEX. They applied four combinations of formation and holding periods varying from 3 to 12 months, which resulted in a total of 16 portfolios with disparate holding and formation periods. The 16 portfolios were based on the best and worst performing deciles that were ranked according to their past performance. The 1993 Jegadeesh and Titman article refer to such strategy as a relative strength strategy, which simply means that the ranking is based on the equities relative performance to the entire sample. They longed the best performing decile and funded the long positions by shorting the worst performing deciles. This way they had an initial investment of zero, hence the strategy is often referred to as a zero-cost trading strategy (even if transactions cost are not included). Based on their empirical research, Jegadeesh and Titman found that by applying a relative strength long-short zero-cost trading strategy that formed momentum portfolios based on six month past price information and held such portfolios for subsequent six month, investors would be able to earn a significant annual abnormal return of 11.40 percent (3.07)[7]. The highest relative strength return was obtained by the strategy that formed portfolios based on 12 months past price information and held such portfolios for subsequent three months, that produced a significant annual excess return of 12.00 percent (4.28). They found that the excess return could potentially be explained by an underreaction to the short run potential of the equities and an overreaction to the long run potential. This way investors would hold on to losing equities in the short-run and sell winners prematurely in the long run. This would impose a short run biased supply of the equity given the equity prices only adjusts slowly to new information due to the underreaction by the investors. This underreaction could, according to Jegadeesh and Titman, cause some predictability in the equity prices. This explanation was later associated with the behavioural studies and the disposition effect (Frazzini, 2006).

Chan et al., 1996 In 1996, Narasimhan Jegadeesh joined Louis Chan and Josef Lakonishok (Chan et al., 1996) in a more varied momentum study compared to the 1993 article as they applied a much shorter sample period from 1977 to 1993. The 16-year sample period was sampled on the exact same data as the 1993 article, yet they extended the data by including all listed equities on the US Technology index NASDAQ. They applied the 1993 Jegadeesh and Titman methodology and found that by ranking equities into portfolios based on their prior six month return, a long-short relative strength trading strategy would produce an annual excess return of 8.8 per cent over the subsequent six months. They found that past returns as well as short term earnings announcement, i.e. earnings surprises, explained much of the future price movements. This was also seen in the 1993 Jegadeesh and Titman article. Moreover, they found that the sub sample did not reverse towards the mean, but rather continued to drift. Furthermore, they applied a three-factor Fama-French model (Fama & French, 1996) to account for eventual size or style bias in the sample, yet they found that neither size nor high book-to-market multiples could explain the abnormal return of the momentum strategy. Eventually, they found that investors perceived new information inefficiently as they were not able to distinguish between crucial and trivial information.

Conrad and Kaul, 1998 In 1998, Jennifer Conrad joined Gautam Kaul (Conrad & Kaul, 1998) in a study of the impact of historical periods on momentum in a US equity market sample. Their primary investment approaches were a momentum strategy and a contrarian strategy both evaluated in the short run and in the long run. The applied data sample was sampled using all listed equities on the NYSE and AMEX on a 64-year sample period from 1926 to 1989. Conrad and Kaul measured the performance of an equity relative to an aggregated market index and formed 120 portfolios with eight different holding periods. The methodology differs from the 1993 Jegadeesh and Titman article, due to the fact that the ranking was not based on deciles, but rather arbitrary performance weights. From the original 120 portfolios only 30 proved to be profitable and only for a period up to 12 months, which was in accordance with the previous literature. They found that the average excess return of the 30 portfolios in the sample period was approximately 8.5 percent (4.55) annually. Furthermore the momentum strategies were not profitable in the sub-period 1926 to 1947 primarily due to the US still recovering from the aftermath of World War I, the economic peril under the equity market on Black Thursday on October 29, 1929 and the Great Depression of World War II. These three major crises in US history all had severe impacts on the capital markets and could potentially have biased any data sample in the period from 1910 to 1950.

Grinblatt and Moskowitz, 1999 In 1999, Tobias Moskowitz and Mark Grinblatt (Grinblatt & Moskowitz, 1999) gathered a data sample consisting of all equities listed on NYSE, AMEX and NASDAQ on a 33-year sample-period from 1963 to 1995. They applied the same methodology as the 1993 Jegadeesh and Titman article and based the momentum portfolios on a six month formation period followed by an six month holding period. It has to be noticed that the best performing equities and worst performing equities were not ranked based on equally weighted deciles. Instead, Moskowitz and Grinblatt based their ranking on the more liquid 30 percent best performing equities and more liquid 30 percent worst performing equities to make the entire data sample more liquid. Antagonists of the previous relative strength studies have previously claimed that decile ranking made the sub-samples very illiquid, especially in the lowest performing deciles. They found that by applying a relative strength long-short zero-cost trading strategy, an investor would be able to earn a significant excess monthly return of 0.43 percent (4.65) or approximately 5.2 percent annually. If they adjusted for the industry component, the investment strategy became evidently much less profitable. This indicated that equity market momentum has a potential industry bias. The industry bias is even more evident if the investment strategy screens on industries rather than ISIN-codes (raw equity). Such method lead to the conclusion that the best and worst performing equities were clustering in industries.

Jegadeesh and Titman, 2001 In 2001, Narasimhan Jegadeesh and Sheridan Titman (Jegadeesh & Titman, 2001) extended their 1993 study to a broader sample period and included all equities listed on NASDAQ as well. The 25-year sample period applied in the 1993 study was extended by 10 years to include 1998. They found analogously to their 1993 study that by forming momentum portfolios based on a six month formation period and a subsequent six month holding period, such strategy would earn a significant monthly abnormal return when trading the long-short zero-cost portfolio. The 34-year sample period produced a monthly excess return of 0.86 percent (4.34) corresponding to an annual excess return of 10.3 percent in the large cap segment. The small cap segment has a monthly excess return of 1.42 percent (7.41) and combining large and small cap would yield an excess return of 1.23 percent (6.46). These findings indicated that price momentum could be driven by size factors. They joined the conclusion of previous literature that the existence of equity market momentum existed due to an underreaction to idiosyncratic information where investors tended to ride their losses and realise their gains. The evidence of the *disposition effect*, shown in section 2.2, was prominent in the 2001 study as they found significant negative abnormal returns in the post-formation horizon supporting the tendency that investors realise gains prematurely.

Grundy and Martin, 2001 The same year, Bruce Grundy and Spencer Martin (Grundy & Martin, 2001) introduced the application of a multi-factor approach on a US data sample based on the 2001

Jegadeesh and Titman sub sample. The 70-year period was the second longest sample period in the academic research of price momentum. They applied the same selection criteria as the 1993 and 2001 Jegadeesh and Titman studies and longed the best performing deciles while shorting the worst performing deciles respectively. They found that a six month held long-short portfolio based on six month past price information earn a monthly excess return of 0.44 percent (1.83), which corresponds to an annual excess return of 5.3 percent. This way, the excess return remains only significant at a 90 significance level, contrary to the traditional 95 or even 99 significance level. The crucial findings from Grundy and Martin were their application factor analysis. They composed a two-factor and a three-factor and found that by adjusting for Fama and French's three factors, a relative strength momentum strategy would produce a highly significant monthly return of 1.34 percent (12.11). They further found that the profitability of the momentum strategy was neither due to cross-sectional variability in the return nor due to industry bias, which is contradictory to previous academic research made on the US equity market (Grinblatt & Moskowitz, 1999).

The European Evidence

Rouwenhorst, 1998 One of the pioneers in the academic research on relative strength equity market momentum in European equity samples was Geert Rouwenhorst (Rouwenhorst, 1998). In 1998 he sampled 2,190 equities listed in 12 different European equity markets over a 16-year sample period from 1980 to 1995. He duplicated the methodology of previous research (Jegadeesh & Titman, 1993) and found that by following a long-short zero-cost fading strategy that ranked the best and worst performing equities into deciles, investors would earn a significant abnormal return of 1.16 percent (4.02) after adjusting for size and market risk. This corresponds to an annual excess return of 13.9 percent. He based his evidence on a six month held portfolio based on a six subsequent formation periods. He further found that the persistence of the momentum lasted about one year and supported previous research on strong small cap momentum (Jegadeesh & Titman, 2001). Furthermore he found a strong significant correlation between the the European equity market momentum and the US equity market markets momentum, and proposed that a mutual intercontinental momentum factor may exist even though he never elaborate further on this specific point.

Liu et al., 1999 The following year, Weimin Liu, Norman Strong and Xinzhong Xu (Lui et al., 1999) applied the 1993 Jegadeesh and Titman methodology to an UK sampled on 2,434 listed equities at The London Stock Exchange during a 20-year sample period from 1977 to 1996. The methodology corresponded to previous academic momentum research, though instead of using monthly performance data they chose to use weekly return data. This made their findings more robust since more portfolios could be constructed. They claimed that by applying a relative strength zero-cost trading strategy based on a 12 month formation period and subsequently held for 3 months, investors would obtain an annual excess return of 23.3 percent (5.45). They found that if investors separately controlled for neither the systematic β, size bias or style bias the alpha would not be eroded, but remain significant and positive. Lastly they found, contrary the the US data samples that momentum alpha is not due to underreaction to industry- or idiosyncratic information as has been postulated in previous articles of US momentum evidence. This evidence shows that the applied data sample does not alter the overall conclusion of short run momentum, yet it does not support the source of it.

Djik and Huibers, 2002 In 2002, Ronald van Djik and Fred Huibers (Dijk & Hiubers, 2002) duplicated the 1998 Rouwenhorst study using a 13-year sample period from 1987 to 1999 that sampled an unstated number of equities listed from 15 different European equity markets. They supported the previous evidence on intermediate term relative strength momentum in the European sub sample and found that by using a six month price biased portfolio held for six month would annually yield an excess return of 7.6 percent. They further suggested that investors tend to underestimate the earnings announcements between two consecutive years and stress that the underreaction factor should be the point of interest for any subsequent studies.

Nijman et al., 2004 The following year Marno Verbeek and Theo Nijman joined Laurens Swinkels (Nijman et al., 2004) to replicate the 1993 Jegadeesh and Titman study using a 11-year sample period from 1990 to 2000. The data was sampled on equities covered by Morgan Stanley at the time of the analysis and consisted of a total of 1,581 equities sampled in 15 European countries. Similar to previous academic studies, they used the methodology of Fama and French as well as divided the data sample into industries or countries in order to be able to explain the excess momentum return. They found, that the momentum strategy produced an annual excess return of 9.7 percent (1.84), but not significant on the 95 percent significant level. Furthermore the article found in contrast to previous studies that momentum could neither be significantly explained by industries nor by countries. With respect to style and market capitalisation they found a tendency that small cap growth equities profited from momentum compared to large cap value equities. These findings supported previous research made on equity size and the explanatory power of industries (Grundy & Martin, 2001).

3.2 Momentum in Exchange Markets

Okunev and White, 2003 As section 3.1 made evident, equity markets momentum have during the last couple of decades been frequently supported. A relatively new phenomenon in the momentum literature is an altered focus from financial assets to more complex asset classes such as currencies. One of the earliest articles published on momentum in exchange rates was the 2003 Derek White and John Okunev (Okunev & White, 2003) article that applied the base methodology from the 1993 Jegadeesh and Titman article (Jegadeesh & Titman, 1993). They applied a 26-year sample period from 1975 to 2000 from eight time series of spot exchange rates. They based the trading rule analogously to the 1993 Jegadeesh and Titman article, yet they did not base the initial ranking on the best and worst deciles of the sample, but according to the best and worst $\frac{1}{7}$th. Their objective initially was to identity the most and least attractive currencies, respectively. They did not base such decisions on past price information, but on a moving average trading rules, that would take positions subject to the volatility. The moving average rule was defined as a short run MA (1 to 12 month) less a long run MA (2 to 36 month) where the most volatile exchange rate would be the most desirable and the least volatile would be the least desirable. Positions in the currencies are taken through futures and held for one month. The portfolios were approximately turned four times a year. They found that in each of the eight exchange rates, momentum was significantly evident with the USD for example earning an annualised momentum alpha of approximately 6.1 percent (1.97). They concluded that investors would be able to significantly earn an excess return using their moving average trading strategy.

Serban, 2010 In 2010, Alina F. Serban (Serban, 2010) composed a trading strategy that, as the 2003 White and Okunev article, was not based on past returns, but on the deviation instead. Contrary to the moving average approach in White and Okunev, this article based momentum on cross-sectional deviations from the Uncovered Interest Parity, which states that if an investors establishes a loan in his or her home currency and lend foreign currency with a higher interest rate than the expected return, ceteris paribus, it should be zero due to the adapting exchange rates. This however tend not always to be the case. They applied a 30-year data-sample from 1978 to 2008 using 10 time series of exchange rates. Using the 1993 Jegadeesh and Titman methodology (Jegadeesh & Titman, 1993) they found that if investors were ranking the currencies based on their deviations from the UIP, a long position in the exchange rate with the highest cumulative return and a short position in the exchange rate with the lowest cumulative return based on the past six month data would earn an abnormal return of 11.2 percent if such a portfolio was subsequently held for six months. They concluded that using time series equity momentum methodology in the currency markets evidently had several similarities with the inefficient equity markets.

Menkhoff et al., 2012 One of the most recent publications on currency market momentum is the December 2012 article by Lukas Menkhoff, Maik Schmeling, Lucio Sarno and Andreas Schrimpf (Menkhoff et al., 2012). They applied a 35-year data sample from 1976 to 2010 on 48 global exchange rates. They based their decision rule on a buy (sell) signal of the profitability of the past months buy (sell) signal, e.g. if it was profitable to sell USD last month, it would be done again this month. The Jegadeesh and Titman methodology was furthermore applied in this study, yet the ranking was based on the best and worst 1/6 of the sample. They found significant cross-sectional profitability of applying a long-short zero-cost trading strategy based on the past six month and held for subsequently six months. They found an average return of 3.66 percent (2.06) that could not be related to traditional risk factors.

3.3 Momentum in Bond Markets

Gebhardt et al., 2005 As section 3.2 and section 3.1 indicated, if investors would invest cross-sectionally in a data sample based on either equities or currencies, they could profit significantly from applying a zero-cost trading strategy. One asset class, where the momentum literature is not very well documented is the debt asset class. One of the first academic studies that joined momentum investing in bonds was the 2005 William R. Gebhardt, Soeren Hvidkjaer and Bhaskaran Swaminathan (Gebhardt et al., 2005) article of cross-sectional momentum in a sample of investment graded corporate bonds. They focused on the interrelated effect of corporate bonds and equities postulated that a momentum spill-over effect could be evident from equities to corporate debt. They applied a 24-year sample period from 1973 to 1996 sampling from the Lehman Brothers Fixed Income Database. They applied the conventional methodology applied in momentum studies (Jegadeesh & Titman, 1993) yet they did not find any evidence of momentum in the prices of investment graded corporate bonds. In fact, on a six month formation period, bonds that performed in the top decile were outperformed by the bond that significantly performed in the lowest quartile by annually 1.44 percent (2.59).

Jostova et al., 2010 In 2010, Alexander Philipov joined Gergana Jostova, Stanislava Nikolova and Christof W. Stahel (Jostova et al., 2010) in a not yet published study similar to the 2004 article. Using a 39-year sample period from 1973 to 2011 they supported a previous study of the significance of momentum in corporate bonds. They found, by applying the 1993 Jegadeesh and Titman methodology that investing in the best performing bonds of the past six months and holding such bonds for subsequently one month significant produced excess return to investors. They furthermore concluded that especially in the corporate high yield segment momentum was strong and the latter mentioned trading strategy would produce a highly significant excess annual return of 1.92 percent (8.72). As for the residual rating segment, corporate investment grade, they found that momentum could not significantly be earned as the latter did. Earning only 10 bps (0.91) led to the conclusion that if investors should invest in to the corporate bond segment, they should focus their selection on the high yield segment rather than investment grade.

3.4 Momentum in Commodity Markets

Miffre and Rallis, 2007 In 2007, Joelle Miffre and Georgios Rallis (Miffre & Rallis, 2007) examined a data sample of 31 commodity futures following the relative strength methodology of previous equity research (Jegadeesh & Titman, 2001; Grinblatt & Moskowitz, 1999). They applied a 26-year data sample from 1979 to 2004 based on 31 US commodity futures obtained from Datastream. They deviated from previous momentum studies by forming the momentum portfolios based on their best and worst performing quintiles instead of the traditional deciles due the limited sample size. They found that an investor applying a long-short zero-cost trading strategy would significantly earn an average return of 9.05 percent (2.30) using a six month held portfolio that was based in the past six month past performance. They further found that an equally weighted strategy in all the included commodities would underperform by 2.64 percent, hence allocation to the most efficient commodities were crucial in commodity investing. Finally, they found low correlation between the commodity momentum and equity hence they concluded that momentum would serve las an lucrative overlay in a well-diversified portfolio.

Shen et al., 2007 Later that year, Qian Shen, Andrew C. Szakmary and Subhash C. Sharma (Shen et al., 2007) applied a data sample of 28 commodities during a 45-year sample period sampled from the Commodity Research Bureau. Motivated by the low cost and high availability of short opportunities, they found that a long-short zero-cost trading strategy significantly produced an annualised return of 4.03 percent (3.85) if the long-short strategy was based on the familiar portfolio that is held for six month based on six month past prices. In fact, following a two month formation period, 24 of the total 28 commodities contributed positively to the overall momentum return. They followed the 1993 Jegadeesh and Titman methodology and their findings were in accordance with the related literature on short run and intermediate term momentum persistence in commodity markets (Miffre & Rallis, 2007). They supported previous behavioural findings of momentum existence could be due to an underreaction to market information.

Table 3.1: **Published Momentum Articles**

Table 3.4 exhibits the most significant momentum articles published across the four broad asset classes the past 20 years. F denotes the formation period and H denote the holding period. Significance is reported in brackets succeeding the alphas

Author(s)	**Date**	**Data Sample**	**Sample Period**	**Research Method**	**Portfolio Rank**	**Long-Short Portfolio**	**Annualised Alpha (%)**
Jegadeesh & Titman	1993	NYSE & AMEX	1965 - 1989	JeTi1993[8]	10th	F12 - H3	12.0 (4.28)
Chan et al.	1996	NASDAQ, NYSE & AMEX	1977 - 1993	JeTi1993	10th	F6 - H6	8.8 (n/a)
Conrad & Kaul	1998	NYSE & AMEX	1926 - 1989	CoKa1998[9]	Arbitrary	F9 - H9	8.5 (4.55)
Grinblatt & Moskowitz	1999	NASDAQ, NYSE & AMEX	1965 - 1998	JeTi1993	30th	F6 - H6	5.2 (4.65)
Jegadeesh & Titman	2001	NASDAQ, NYSE & AMEX	1965 - 1998	JeTi1993	10th	F6 - H6	10.3 (4.34)
Grundy & Martin	2001	NASDAQ, NYSE & AMEX	1926 - 1995	JeTi1993	10th	F6 - H6	5.3 **(*1.83)**
Rouwenhorst	1998	12 Euro Markets	1980 - 1995	JeTi1993	10th	F6 - H6	13.9 (4.02)
Liu et al.	1999	London Stock Exchange	1977 - 1996	JeTi1993	10th	F12 - H3	23.3 (5.45)
Djik & Huibers	2002	15 Euro Markets	1987-1999	JeTi1993	10th	F6 - H6	7.6 (n/a)
Nijman et al.	2004	15 Euro Markets	1990 - 2000	JeTi1993	10th	F6 - H6	9.7 **(*1.84)**
Okunev & White	2003	8 Currencies (Time Series)	1975 - 2000	JeTi1993	7th	M.A.	6.1 (1.97)
Serban	2010	10 Currencies	1978 - 2008	JeTi1993	10th	F6 - H6	11.2 (n/a)
Menkhoff et al.	2012	48 Currencies	1976 - 2010	JeTi1993	6th	F6 - H6	3.66 (2.06)
Gebhardt et al.	2005	Lehman Corporate	1973 - 1996	JeTi1993	10th	F6 - H(2,7)	-1.44 **(**-2.59)**
Jostova et al.	2010	Lehman Corporate	1973 - 2011	JeTi1993	10th	F6 - H1	1.92 (8.72)
Miffre & Rallis	2007	31 Commodities	1979 - 2004	JeTi2001[10]	20th	F6 - H6	9.05 (2.30)
Shen et al.	2007	28 Commodities	1959 - 2003	JeTi1993	10th	F6 - H6	4.03 (3.85)

**Insignificant at the 95 percent significance level*

***Significant, yet negative alpha estimates*

3.5 Summary

Chapter 3 illustrated the 17 most prominent momentum articles within the selected four broad asset classes. The findings of the articles are as follows. Jegadeesh and Titman (1993) found a significant alpha of 12.0 percent (4.28) that potentially was driven by the short term underreaction to new information as illustrated in (Frazzini, 2006). This was subsequently supported in Conrad and Kaul (1998) that even applied a larger sample period, thus holding the data sample constant. Conrad and Kaul (1998) furthermore added that the momentum profitability could be limited to exist in extremely negative markets. Grinblatt and Moskowitz (1999) and Jegadeesh and Titman (2001) additionally supported the significant momentum alpha applying a similar data sample as Jegadeesh and Titman (1993). Chan et. al (1996) illustrated that neither the size nor the value factor significantly explained the momentum existence in European equites, which was opposed to Jegadeesh and Titman (2001) that found a significant small cap effect in US equity markets. Such effect was furthermore seen in Djik and Huibers (2002). Moreover, Grinblatt and Moskowitz (1999) added that certain industries would be more likely to exhibit momentum. However, Grundy et al. (2001) did, contrary to Grinblatt and Moskowitz (1999), neither found the equity momentum to be significant nor driven by industries.

Rouwenhorst (1998) as well as Liu et al. (1999) supported the findings of the US equity market on the European equity market. Rouwenhorst (1998) found a high correlation between the US and the European equity market momentum and proposed that a common momentum factor might exist. Liu et al. (1999) supported the findings of the absent small cap and value effects by Chan et. al (1996) that still was rejected by the inaugural momentum study by Jegadeesh and Titman (2001). Nijman et al. (2004) did not find the momentum to be significant, thus supported Grundy et al. (2001) that found a significant dependence to an industry bias. Nijman et al. (2004) further found, contrary to Liu et al. (1999) and Chan et. al (1996) that especially small cap growth equities tend to drive momentum compared to large cap equities.

White and Okunev (2003), Serban (2010) as well as Menkhoff et al. (2012) all support the latter equity market significance as they apply the methodology to currency markets. Serban (2010) found that similar momentum pattern is evident in the currency markets, especially the overreaction the new information. This was furthermore supported by both White and Okunev (2003) and Menkhoff et al. (2012) where the latter stated, in accordance to e.g. Chan et. al (1996) that momentum was not depending on traditional risk factors. Gebhardt et al. (2004) and Jovesta et al. (2011) found that bond rating drove part of the debt market momentum, where high-yield bonds tend to drive momentum compared to investment grade bonds.

Miffre and Rallis (2007) and Shen et al. (2007) supported the subsequent momentum evidence in a commodity market. Miffre and Rallis (2007) added that the correlation structure between commodity momentum and other asset classes tend to be very low i.e. commodity momentum thus serves as a lucrative portfolio overlay.

We can deduce from chapter 3 that the momentum evidence within the four broad asset classes are significant as well as proven. We can deduce that multi-asset momentum, based on the literature review, is plausible, despite the fact that the momentum publication body is not, to the same extend, supported by evidence in debt, currency and commodity markets.

Chapter 4

Data Presentation

Before constructing the momentum model and elaborating on the empirical results in chapter 5, we find it important to present some basic characteristics of the applied data sample. We do this in the first part of chapter 4, with respect to the applied definitions of the broad asset class, as well as the inherent abilities of the applied time series. In the second part, we examine the robustness and validity of the constructed momentum portfolios in chapter 5. To avoid any confusion, we must emphasise, that the second part of chapter 4 is solely intended to support the overall significance of chapter 5, and not elaborate on any momentum results. We acknowledge that this might not be chronological, as the underlying basis of the trading model has not yet been presented. However, we must first accept the assumptions underlying the econometric analysis to strengthen our overall conclusions of the trading portfolios.

The contents of chapter 4 is divided such that section 4.1 illustrates how the four broad asset classes are broken up into 50 sub asset classes as well as the correlation structure between the applied time series. It furthermore exhibits how investors can benefit from such a structure. Section 4.2 presents the five basic assumption of the ordinary least square model that ensures a BLUE-estimation as well as perform the test of the assumption regressed on a six month held momentum portfolio with a six month formation period. We summarise the conclusions in section 4.3. The intention of chapter 4 is to vindicate the application of both the applied data sample as well as the applied momentum portfolios.

4.1 Data on the Applied Time Series

As the previous chapter 3 illustrated in table 3.4, the most significant articles published on short term momentum, within an individual asset class, have predominantly been examined as a part of a US equity carve-out. Yet, as table 3.4 furthermore exhibits, evidence in broad European equity carve outs as well as regional carve outs has additionally proven profitable if an investor applied the zero-cost trading strategy. With respect to the published momentum evidence in other broad asset classes than equity, such evidence is not fully documented. As table 3.4 illustrated, both bond market momentum as well as currency and commodity momentum have been indicated to be profitable in the short term, but evidence is limited. The 17 published articles from table 3.4 all test momentum from a separation perspective, where the momentum evidence is separately examined within each distinct broad asset class. In this thesis, we extend this knowledge and postulate an contiguous theory, where momentum exists across asset classes in a multi-asset environment. We postulate that investors applying the zero-cost trading momentum portfolio, can benefit from the multi-asset relationship in a cross-sectional momentum setting. Where the momentum has been tested cross-sectionally on data-samples consisting of equities, bonds, currencies and commodities, respectively, we postulate that the same methodology can be applied cross-sectionally on a multi-asset data sample. To our knowledge, such trading strategy has only peripherally been mentioned in previously published articles (Moskowitz et al., 2012; Blitz & Vliet, 2008). We find it plausible that constructing a multi-asset data sample, which exploit the cross-sectional arbitrage from shorting past inferior performers to fund long positions in past performers, in addition to potential correlation benefits, would earn a strong and significant alpha. We will denote the sub asset classes as merely asset classes for simplicity. If we refer to a distinct sub asset class or broad asset class it will explicitly stated. The subdivision of the four broad asset classes into 50 sub asset classes follows below. We have listed the number of included sub asset classes in the broad asset classes and the full data sample can be seen from table 4.1:

- **Broad Asset Class I: Equity**
  3 Core Standard Capped Indices
  3 Value Standard Capped Indices
  3 Growth Standard Capped Indices
  6 Fundamental Standard Capped Indices
- **Broad Asset Class II: Commodity**
  20 Commodity sub Indices
- **Broad Asset Class III: Debt**
  2 High Yield Bond Indices
  2 Aggregate Bond Indices
  1 Government Index
  3 Corporate Bond Indices
- **Broad Asset Class IV: Currency**
  7 Leading Exchange Rates

Table 4.1: **Return Statistics of Asset Classes**

	n	Return (%)	Risk (%)	Sharpe*	Max (%)	Min (%)
Natural Gas	145	-23.41	51.58	0.28	48.51	-36.05
Nickel	145	10.14	42.28	0.44	39.22	-28.93
Lead	145	12.89	36.74	0.51	30.36	-37.48
Sugar	145	8.10	36.56	0.35	36.10	-25.62
Cocoa	145	3.29	35.20	0.24	41.43	-20.30
WTI Crude Oil	145	6.60	34.25	0.39	23.62	-34.27
Heating Oil	145	10.44	33.82	0.48	26.45	-27.72
Cotton	145	-8.56	32.97	0.12	37.5	-20.76
Coffee	145	-11.51	32.07	0.12	32.86	-21.81
Zinc	145	0.14	31.82	0.16	27.63	-25.21
Wheat	145	-9.68	31.08	0.20	36.06	-21.83
Copper	145	12.14	31.06	0.52	30.93	-27.21
Corn	145	-7.43	31.00	0.10	29.64	-30.68
Silver	145	13.14	30.95	0.55	20.68	-28.15
Tin	145	11.78	26.45	0.53	27.77	-20.82
Platinum	145	13.52	25.75	0.63	26.96	-30.99
Lean Hogs	145	-11.93	25.21	0.31	25.31	-21.43
KIX Emerging Markets Growth	145	4.72	25.08	0.34	16.27	-31.30
MSCI Emerging Markets Growth	145	5.78	24.99	0.39	16.27	-27.61
MSCI Emerging Markets	145	7.77	24.46	0.46	17.08	-27.36
MSCI Emerging Markets Value	145	9.75	24.19	0.54	17.90	-27.13
KIX Emerging Markets Value	145	15.54	23.18	0.77	20.74	-22.73
MSCI Europe Value	145	1.68	22.24	0.21	19.79	-22.61
Aluminium	145	-1.09	22.14	0.06	19.30	-24.06
KIX Europe Value	145	6.55	20.95	0.43	18.82	-22.79
MSCI Europe	145	0.93	20.20	0.18	13.94	-21.24
MSCI Europe Growth	145	-0.05	19.00	0.14	12.20	-19.91
Barclays European High Yield	145	7.47	18.74	0.48	22.13	-24.24
KIX North America Value	145	5.93	18.59	0.41	17.47	-15.15
KIX Europe Growth	145	0.25	18.50	0.13	11.05	-21.25
MSCI North America Growth	145	-1.69	18.16	0.04	11.87	-19.04
MSCI North America Value	145	1.47	16.67	0.17	10.70	-16.88
MSCI North America	145	0.08	16.56	0.12	10.89	-17.96
Gold	145	13.00	16.27	0.80	13.19	-11.65
KIX North America Growth	145	-0.22	15.52	0.06	11.48	-17.78
Cattle	145	-2.02	15.07	0.06	10.99	-19.20
AUD/USD	145	3.81	13.63	0.36	9.69	-16.79
BofA Emerging Market Corporates	145	9.16	12.52	0.78	11.29	-29.92
SEK/USD	145	1.83	12.47	0.20	10.30	-10.75
Barclays Euro-Aggregate Corporate	145	6.95	12.43	0.59	10.19	-11.58
Barclays Euro-Aggregate	145	7.12	11.80	0.63	10.67	-9.32
CHF/USD	145	4.57	11.35	0.44	13.22	-10.66
Barclays US Corporate High Yield	145	7.20	10.95	0.69	12.10	-15.90
EUR/USD	145	2.17	10.94	0.24	9.54	-9.72
CAD/USD	145	3.05	9.61	0.37	8.78	-13.87
JPY/USD	145	2.40	9.59	0.29	7.94	-8.21
GBP/USD	145	-0.28	9.09	0.02	9.32	-9.33
J.P. Morgan EMBI Diversified	145	10.66	9.03	1.19	7.45	-16.03
Barclays US Corporate	145	7.39	6.42	1.12	7.28	-8.26
Barclays US Aggregate	145	6.43	3.64	1.69	3.73	-3.36

**Risk-free rate = three-month US Treasury Bill*

Of the entire data sample, 30 percent of the data sample consist of equity indices in various style biases (as well as regional biases), 40 percent of the data sample consist of individual commodities, 16 percent of the data sample consist of debt indices in various ratings (as well as regional biases) and 14 percent of the data sample consist of regional exchange rates. We assume, that the data sample reflects a real life multi asset investment portfolio, as *"multi-asset managers frequently have high allocations to the equity and the commodity segment"* (Wind, 2012). The number of indices are, to some extent, selected arbitrarily, however given the frequent high allocation to the equity and commodity segment in addition to the magnitude of published articles on these two broad asset classes, we find a 70 percent allocation in our data sample can be justified. Furthermore commodities as well as equities are among the most discussed asset classes in the investment industry during the past decade. The remaining 30 percent is allocated to debt and currencies due to the limited published evidence on profitable and significant momentum in such broad asset classes. The applied time series are, in a real life setting, composed by traded individual future contracts. *"Given that multi-asset managers often turn their portfolio up to 300 times a year"* (Wind, 2012), constructing the times series ourselves is far beyond the scope of the thesis. This was also explicitly written in section 1.3. This way, the applied data sample can be examined as balanced panel data with 144 observations, which tend to increase the robustness of the empirical findings.

We use conventional equity indices offered by Morgan Stanley Capital International *(MSCI)* and produce the fundamental equity indices using the conventional MSCI data, applying the methodology in section 2.4.3. The bond indices are offered by Bank of America, previously Merrill Lynch *(BofA Merrill Lynch)*, *J.P. Morgan* and *Barclay's Capital*. The commodity indices and individual currencies are offered by UBS in co-operation with Dow-Jones *(DJ-UBS)*. All exchange rates have USD as foreign currency. The majority of the indices are rebalanced semi-annually to avoid any survivorship bias. The total return data is obtained from Thomson Reuters Datastream and Bloomberg, which has been applied in several of the academic studies from table 3.4. The data sample is obtained as total returns from the last trading day of each month and equity prices have been adjusted for corporate actions as splits and dividends by Morgan Stanley. The choice of using monthly data is based on the fact that this thesis does not apply to day-traders, but to investors with intermediate term investment horizons up to 12-months. All returns are converted into USD to ensure that no currency rewards are withheld in the returns (Sercu, 2009). This way, we periodically apply the wording *exchange rate* to the currency asset class. We furthermore subtract a three-month risk free US Treasury Bill as we are interested in the return generated above the risk free rate of return. With respect to the sample period, we have been limited by shortcomings in relation to the number of observation in the applied data sample. For example, the selected commodity indices are only available from the start of 1999 and most emerging market debt indices are only available from the end of 1999. This limit the number of possible observations in the commodity and debt carve-outs hence the sample period is far shorter than in previous published articles. The data period starts at the end of December 1999 and ends at the end of December 2011. Finally, instead of trading in and out of low priced future constructs, we assume that trading in and out of low priced exchange traded funds will be a feasible option.

4.1.1 Correlation Structure

An important feature of multi-asset investing is the diversification and correlation benefits from trading in the four broad asset classes that have the ability to boost the long-short positions in a given trading portfolio. Investors invested in long-short portfolios have the ability to profit from both down-markets as well as up-markets given the right allocation with respect to correlation and diversification. For example, in an extreme case, sub asset class I is perfectly negatively correlated to sub asset class J. If sub asset class I decreases in value, investors should expect sub asset class J to increases in value and vice versa. In an optimal scenario, we want the correlation to be close to zero in long-only portfolios and negative in long-short portfolios (given we have allocated correctly into the various asset classes). The overall motive for multi-asset investing can be illustrated in table 4.1.1. We have only shown a small subset of the total indices as we assume it will be representative of the overall data sample.

Generally speaking, we expect the correlation between debt and equity to be moderate and the correlation between commodities and especially equities to be very low. The expectations is based on the fact that we assume the frequent allocation to equity and commodities in multi-asset portfolios must be vindicated by interrelated correlation potentials. We assume domestic exchange rates to a have high correlation to domestic debt (i.e. the danish currency is highly correlated to danish bond indices) and low correlation to overall equities. Table 4.1.1 exhibits the results. The equity markets tend to have high correlation to each other, indicating that equity markets could be driven by some of the same factors. Debt indices are moderately correlated to both equities and to each other, which indicates that equity markets and regional debt indices are not much affected by the same factors. It is surprising that US bonds are negatively correlated to equities which indicates that US bonds potentially could be lucrative in momentum portfolios in the sample period. Currencies have low correlation to equities, debt and to other currencies, yet domestic (or pseudo-domestic) currencies have extremely high correlation to domestic debt indices. Commodities have close to zero absolute correlation to both equities and debt, which underline the importance of allocating a high share to equities and commodities.

Table 4.2: **Subset Correlation Structure**

Table 4.1.1 illustrates the correlation structure of a subset from the data-sample. We use the notation in the first row as follows: EME=Emerging Markets Equity, EUE=European Equities, USE=US Equities, EMD=Emerging Aggregate, EUD=European Aggregate, USD=US Aggregate, CHD=CHF/USD, EUD=EUR/USD, GBD=GBR/USD, GLD=Gold, WHT=Wheat and WTI=WTI Crude. The correlation covers the 12-year sample-period from December 1999 to December 2011.

	EME	**EUE**	**USE**	**EMD**	**EUD**	**USD**	**CHD**	**EUD**	**GBD**	**GLD**	**WHT**	**WTI**
Equities												
Emerging Markets	1.000											
Europe	**0.849***	1.000										
North America	**0.820***	**0.881***	1.000									
Fixed Income												
Emerging Markets	0.648	0.587	0.551	1.000								
Europe	0.355	0.481	0.238	0.457	1.000							
North America	**-0.01**	**-0.00**	**-0.07**	0.525	0.503	1.000						
Currencies												
CHF/USD	0.262	0.387	0.157	0.262	**0.829***	0.300	1.000					
EUR/USD	0.427	0.566	0.322	0.411	**0.960***	0.328	**0.856***	1.000				
GBP/USD	0.357	0.438	0.253	0.264	0.573	0.142	0.528	0.613	1.000			
Commodities												
Gold	**-0.10**	**-0.09**	**-0.13**	**-0.03**	**0.105**	**0.041**	0.189	0.260	0.319	1.000		
Wheat	**-0.02**	**-0.06**	**-0.04**	**-0.06**	**-0.04**	**-0.11**	0.291	0.333	0.384	0.253	1.000	
WTI Crude	**-0.01**	**-0.01**	**0.001**	**-0.00**	**-0.05**	**-0.11**	0.671	0.640	0.674	0.187	0.234	1.000

**Extreme dependence*

4.2 Data on the Applied Portfolios

4.2.1 Econometric Testing

We will, in the remainder of this chapter, examine the validity and reliability of the produced long-short trading portfolios in chapter 5. We find it important to test a number of standard assumptions behind the ordinary least square estimation as our conclusions will rely on these estimates. Particularly, the econometric issue of accuracy is vital, why we need to restrict the analysis to enable valid results. In order to be able to postulate the results as being significant, we furthermore have to ensure that the consistency of the analysis is high. Thus, solely running an ordinary least square regression is not sufficient for ensuring a reliable relation between the model and the model variables. The produced trading portfolios are tested on the basis of five standard assumption that set the basis of the best ordinary least square estimation. The standard ordinary least square regression can be expressed in equation 4.1.

$$y = \alpha + \beta_1 x_1 + ... + \beta_n x_n + \epsilon \tag{4.1}$$

where α defines the graphically intercept, i.e. the value of y, given all model parameters are equal to zero. The β_n defines the expected change in y as x changes by one. In a univariate setting, β is the slope of the ordinary least square estimation. ϵ is the error term and defines the part of the variation in y that are not explained by any of the model parameters. Equation 4.2 is similar to equation 2.8 and illustrates a random walk process with identical, independent and normally distributed error terms with a mean zero and a equal variance.

$$\epsilon_i = IIDN(0, \sigma^2) \tag{4.2}$$

Following equation 4.1, and the standard assumptions outlined below, we are able to determine the validity of the regressed results. The standard assumptions are presented in this subsection and tested in subsection 4.2.3. We will limit our tests to consist of broadly accepted tests commonly applied in econometric analysis. We acknowledge that further tests can be applied, yet we find this to be beyond the scope of the thesis. The five standard assumptions are randomly listed below:

- **Linearity**
  Linearity of the model parameters
- **Normality**
  Normally distributed model error terms
- **Homoscedasticity**
  Equal variance in model error terms
- **Independence**
  Uncorrelated model error terms
- **Multicollinearity**
  Uncorrelated model parameters

Given that the five standard assumption are fulfilled, the ordinary least square estimation is said to be BLUE (Best Linear Unbiased Estimation). An ordinary least square estimation is based on minimising the gap between the residuals and the estimated regression line with the intercept α and slope β. The choice of testing the long-short trading portfolios on the basis of an ordinary least square model is based on its frequent application in modern financial studies hence we assume that the method is accurate. We use SAS 9.2 for the econometric analysis as Excel is not an optimal environment for statistical analysis.

Finally, it has to be emphasised that this section is not meant to be an exhaustive econometric analysis, as this is considered to be beyond the scope of the thesis. The section is meant to contribute to the underlying abilities and weaknesses of the long-short trading portfolios and to support the significance of the results from chapter 5.

We test the five assumptions on every long-short zero-cost trading portfolio constructed in chapter 5, yet only the six month held portfolio that is based on past six month prices is reported. The entire data sample is seen in table 4.1. The choice of isolating of the 6-6 portfolio is based on the resemblance between the such portfolio and the average of all portfolios. This way, we find the results of the 6-6 portfolio is representative of the results of the 25 portfolios.

We will test the assumptions using six factors as independent variables. Theses are the Fama-French's size factor (SMB), style factor (HML) and equity market factor (MKT) as well as Carhart's momentum factor (UMD), the bond factor (BOND) and the commodity factor (DJUBS). We use theses factors due to their application in previous multi-asset articles from chapter 3 as well as their application to the factor analysis in chapter 5.

4.2.2 Econometric Assumptions

Linearity As the ordinary least square estimation is related to linear regression, violation of the linearity assumption basically mean that we test non-linear data in a linear environment. For example,a β^2 or ϵ^2 would violate the linearity assumption and would bias the predicational power of the overall model. Basically, the linearity assumption means that the model follows equation 4.1. As factor models are frequently applied in the investment industry, we assume that the linearity assumption is fulfilled, hence we will not test this assumptions any further.

Normality The assumption of normally distributed error terms follows from equation 4.2. Violations can compromise the beta estimates and confidence intervals causing unreliable t-statistics. It must be noticed that moderate deviations from the normality assumption will generally be accepted. We will test the normality assumption using the *Anderson-Darling test*. The test is based on a standard p-value and values ≥ 0.05 indicates a normal distribution of the error terms.

Homoscedasticity Having heteroscedasticity in a model, as opposed to having homoscedasticity, normally entails that the residual variance is dependent on the size of the variables. Due to a heteroscedasticity bias, we will test for equal variance in the model to ensure that residuals are constant over time. We test the homoscedasticity assumption using *White's t-test*. The test is based on a t-statistics, that have to be ≥ 2.492 (3.880) at a 95 percent (99 percent) significance level to allow us to accept the hypothesis of equal variance. If the t-statistic is significant, it indicates that the residual variance is equal and constant over time, i.e. homoscedastic.

Independence Independent distributed residuals means that there are no serial correlation in the residuals, i.e. no autocorrelation. Violations of the independence assumption is most commonly detected running either a *Durbin-Watson or a Ljung-Box test*. The fundamental difference between the Durbin-Watson test and the Ljung-Box test lies in the fact that the former solely test the one period autocorrelation and the latter tests on multi-periods, i.e. the overall randomness. The Durbin-Watson test separates itself from conventional hypothesis tests, as the determination of autocorrelation is based on an interval from zero to four and not actual distributions. A score between one and three indicates that the model has no residual autocorrelation and a score less than one or higher than three indicates residual autocorrelation. Zero autocorrelation is equal to a score of two. The Ljung-Box test is more refined than the Durbin-Watson test as it is based on several lags. We test the Ljung-Box from one month up to three years. The Ljung-Box test follows a χ^2 distribution and the score has to be ≥ 2.71 (3.84) to allow us to accept that the residuals have no autocorrelation at a 90 percent (95 percent) significance level.

Multicollinearity In case of two or more independent variables being too highly correlated, we potentially have a multicollinearity issue that can cause inferior model estimations. Normally, a correlation coefficient of .80 is regarded to cause multicollinearity. Given that multicollinearity is detected in the data-sample, it does not mean the variables does not explain a significant amount of the variation in the dependent variable. It simply means that the two independent variables are doing part of the same thing in the regression. Having multicollinearity means, that the significance of the beta estimates are not reliable. A formal method for detecting multicollinearity is the calculation of the *Variance Inflation Factors* (VIF) for the individual independent variables. If the VIF-score > 10, the model parameters are too highly correlated. A VIF-score of ten is essentially the same as an R^2 of .90.

4.2.3 Econometric Evidence

SAS on Normality As figure 7.5 exhibits, a portfolio held for six month based on the previous six month information regressed on the Fama-French size factor (SMB), style factor (HML), and market factor (MKT) as well as Carhart's momentum factor (UMD), the bond factor (BOND) and the commodity factor (DJUBS), have a Anderson-Darling t-statistics equal to 1.2765. This allows us to conclude, on a 95 percent significance level that the error terms are normally distribution and we do not have any issues with the normality assumption. We assumed that the Anderson Darling-statistics is sufficient for testing the normality assumption in this thesis.

SAS on Homoscedasticity As figure 7.7 exhibits, both the commodity factor (DJUBS), the size factor (SMB), the momentum factor (UMD) as well as the market factor (MKT) are all significantly higher than the critical values of 2.492 (3.880). We can conclude, on a 99 percent significant level, that the residual variance is equal and constant over time and the model is not influenced by heteroscedasticity. The reminding style factor (HML) and bond factor (BOND) are significant at a 5 percent significance level.

SAS on Independence As figure 7.6 exhibits, a portfolio held for six month based on the previous six month information regressed using the previous listed six factors have a Durbin-Watson t-statistics of 1.9887, which is close to the zero autocorrelation score of two and not near the critical scores of one and three. Furthermore the Ljung-Box test from table 7.1 indicates that all of the χ^2-statistics are far ≥ 2.71 (3.84), which is in accordance to the Durbin-Watson result. Based on the two test, we can conclude that the time series are not biased from residual autocorrelation and residuals can be assumed to be independent distributed.

SAS on Multicollinearity As figure 7.8 exhibits, a portfolio held for six month based on the previous six month information has no issues towards multicollinearity, i.e. too high correlation among the independent variables. All VIF-scores lies around 1.10 which corresponds to a R^2 of .10. The independent variables are not subject to further tests.

Consistency with other factors The test has furthermore been applied to the regression that includes the VIX, a TED spread, a CPI factor as well as a CTA factor and the results have proven to be just as strong. Thus we found a high correlation between the VIX factor and the market factor, yet lower than the VIF=10. These tests have not been disclosed in this thesis as we assume the output in chapter 7 sufficiently illustrate the overall conclusion.

4.3 Summary

Chapter 4 illustrated the basis for including the 50 asset classes as well as the expected accuracy of the results from the factor analysis in chapter 5. With respect to the 50 asset classes, they are primarily included based on the significant findings from table 3.4 in chapter 3 on price momentum. The momentum anomaly is evidently strong in all four broad asset classes, thus we expect the potential of a multi-asset momentum to be plausible. Furthermore, given the beneficiary correlation structure between commodities and equity from table 4.1.1, as well as the statement from (Wind, 2012), the initial data sample consists of 70 percent equity and commodities and 30 percent bonds and currencies. In addition, this is based on the disadvantageous high correlation between the currency and debt asset classes.

With respect to the expected accuracy of the results from the factor analysis, five basic assumption of the ordinary least square estimation was tested using SAS 9.2. To primary ensure valid beta estimates as well as unbiased residuals we tested if the model complied with the assumptions of linearity, normality, homoscedasticity, independence and multicollinearity. Following the results from listed in chapter 7, the Anderson-Darling test-statistic of 1.2765 indicated that the model would neither have significantly abnormal residuals nor be biased from homoscedasticity following the various White test-statistics. Furthermore, the residuals should be expected to be independent as both the Durbin-Watson test-statistic of 1.9887 as well as Ljung-Box test-statistics significantly exceed the critical values of 2.71 (3.84). Finally, the independent variables are not biased from multicollinearity such that none of the included factors affects each other significantly. The VIX, TED-spread, CTA-index as well as the CPI-index indicated the same results, yet moderate correlation was found between the VIX and the MKT factor.

We can deduce from chapter 4 that the inclusion of the 50 asset classes is supported by both the correlation structure as well as the evidence on momentum significance. Additionally, we can deduce that none of the factor model included in chapter 5 are significantly biased from neither the linearity, normality, independence, unequal variances nor multicollinearity. We thus consider the data sample to be valid and reliable.

Chapter 5

Multi-Asset Momentum

Chapter 5 will introduce the empirical part of this thesis. We will utilise the knowledge gathered from the former chapters and conduct the empirical study following the most influential momentum study from 1993. As we are working on a multi-asset approach, as opposed to the traditional single asset approach, we will diverge from the traditional methodology, thus maintaining the core stages of constructing the zero-cost trading strategies. The chapter will, first and foremost, present the cross-sectional multi-asset performance on all the 25 zero-cost trading strategies, produced by the momentum model and the inherent significance in each of the individual broad asset classes. The chapter will furthermore elaborate on a subset of five diagonal portfolios to broaden the risk-return relationship with respect to both absolute performance measures as well as relative performance measures. We will additionally extend the knowledge of factor models to explain the impact of both traditional internal factors as unconventional external factors. We will test the out of sample performance to define potential environment, that drives the momentum return. Finally, we will present some empirical issues setting up our trading strategy as well as support the findings by a robustness check.

The contents of chapter 5 is divided such that section 5.1 presents the methodology for constructing the zero-cost trading portfolio as well as the basis of the constructed momentum model. Section 5.2 presents the momentum results on all four broad asset classes as well as the aggregate multi-asset data sample. Section 5.3 presents the two factor models that have the potential of explaining the excess momentum return. Section 5.4 presents the out of sample performance and section 5.5 presents the practical issues on running the investment strategy. Section 5.6 is the robustness test and we summarise the conclusions in section 5.7.

5.1 Methodology

5.1.1 Portfolio Formation

The applied methodology, for modelling the momentum model, is based on the 1993 Jegadeesh and Titman article from chapter 3. The decision criteria for selecting the past best and worst performing asset classes, respectively, are based on a *J-month* period called the **formation period**, often referred to as the look-back period. Each *J-month*, all asset classes are ranked descending on the basis of their individual *J-months* performance. To ensure liquidity in the portfolios we bundle the individual asset classes in quartiles (in addition to Jegadeesh and Titman, who used deciles). This way, the model produces four quartiles, representing the performance of each of the 50 asset classes. After the initial formation, each asset class is ranked based on their past returns and individually bundled in each of the four quartiles. All asset classes from the best quartile are bundled in one portfolio (the winners), all the asset classes in the middle quartiles are bundled in two portfolio (the in-betweeners) and all the asset classes in the worst quartile are bundled in one portfolio (the losers). After the end of a formation period an investors would be faced with four investable portfolios. The formation period of *J-months* is divided in 1, 3, 6, 9 and 12 months intervals.

5.1.2 Portfolio Holding

The subsequent period, following the *J-months* formation period, is a *K-month* period called the **holding period**. This holding period is the alpha period, as an investor would be generating his or her momentum performance in this period. The *K-months* in the holding period are divided the, same way as the formation period, in 1, 3, 6, 9 and 12 months. The performance of the four quartile portfolios is calculated as a geometric average on the produced time series. This way, investors are able to construct 25 combinations of *J-month* formation and *K-months* holding, which allow investors to indicatively access the most profitable portfolio combinations in a data sample. We construct a total of 75 portfolio combinations being 25 winner portfolios, 25 loser portfolios and 25 long-short portfolios. This makes the evidence more robust with respect to only constructing one portfolio combination. As the scope of the thesis is to investigate the significance of a relative strength multi-asset momentum, the portfolios two and three (the in-betweeners), are left out of the analysis. We will occasionally use the 6-6 portfolio as a benchmark for the multi-asset momentum, which is based on the decisions from chapter 4.

5.1.3 Portfolio Positions

Following the *K-month* holding period, investors are able to take positions in the best and worst performing quartiles. The construction of the long-short zero-cost trading portfolios are carried out as follows. If an investor seeks to measure the momentum in a given data sample, given a distinct formation and holding period, he or she should take a long position in the best performing asset class and fund the long position by shorting the worst performing. This was in section 1.2 as the momentum strategy. As the individual asset classes are ranked with respect to the relative performance we call such strategy a relative strength strategy. According to the literature, if an asset class has performed relatively well in the past, we would expect such an asset class to continue to perform relatively well. In this case, we long the asset class to capture the upside of the investment. This is opposed to those asset classes that have performed relatively poor. According to the literature, we would expect that such asset classes will continue to perform relatively poor. In this case, we short the asset class to capture the downside of the investment. In this thesis, we define the best relative performing asset classes as belonging to the top quartile of the data sample and the worst relative performing asset classes to be the lowest quartile of the data sample. Buy positioning long in the best performing quartiles and short in the worst performing quartiles, investors should expect an abnormal return with respect to a long-only portfolio in the best performing asset classes, given the quartiles are drifting. We denote such a long-short investment a long-short zero-cost strategy, as the long positions are funded by the shorts, hence a zero cash will flow to the investment. The excess performance is often referred to as arbitrage.

5.1.4 The Multi-Asset Model

During the last 20 years of momentum literature, several diverse approaches have been undertaken in the momentum model specification. Thus, we find it important to outline the assumptions and limitations applied in this thesis as the multi-asset momentum model was composed. As section 1.3 in chapter 1 illustrated the overall limitations of the thesis, this section will only illustrate the custom specification made for this specific model.

The first key model specification, that differ from the 1993 Jegadeesh and Titman article lies in the portfolio formation structure. As previously published articles have been dealing with a much greater data samples as well as sample periods, they could allow themselves to rank securities into deciles. Due to the limited sample period in this thesis, and to maintain a liquid portfolio approach, the individual asset classes are ranked into quartiles. Ranking 50 asset classes into deciles would mean that the trading portfolios would only consists of approximately five asset classes. Using quartiles, the trading portfolios would approximately consist of more than ten asset classes and more than 20 in the zero-cost trading strategy, which correspond to the number of positions held in a real life multi-asset portfolio. *"Typically around 20 to 30 long and short positions are held within multi-asset portfolios"* (Wind, 2012) to make the diversification more complete.

Another key model specification that varies among the previous academic studies, is the one month lagged period between the formation and the holding period, for example applied in the 1993 Jegadeesh and Titman study (Jegadeesh & Titman, 1993). The inclusion of a lagged period would theoretically ensure that the prices were not driven by any bid-ask pressure and would yield a both stronger and more significant momentum profit. Some of the subsequent published articles concurs with the lagged period, however, not all find it important. This thesis will only include the lagged period methodology as robustness check of the alpha estimates due to the inconclusive effect of having lagged portfolios.

Another model specification, is the decision of overlapping periods. This is as contrast to the 1993 Jegadeesh and Titman study (Jegadeesh & Titman, 1993), not applied in this thesis. Using overlapping periods, investors are able to increase the statistical significance of the tests, since more portfolios can be constructed using the same data sample. However, one potential downside to overlapping periods, is that it create immense transactions cost, as portfolios has to be bought and sold continuously. Since the scope of this thesis is to present an applicable way of exploiting momentum profitably, constructing portfolios too often is assumed to be too costly, despite the fact that we acknowledge it would have increased the significance of the overall multi-asset momentum evidence.

Additionally, the return calculation is furthermore a key model specification. As the individual asset classes are bundled into portfolios based on their past monthly returns, the mean returns are calculated as a simple mean, hence the arithmetic and the geometric mean do not diverge. However, calculating the mean return of the four portfolios, a more sophisticated return calculation must apply. Due to the fact, that arithmetic means lack the compounding effect of historical data, the geometric mean is applied in calculating the average return of a given portfolio. Jegadeesh and Titman used an arithmetic mean in their 1993 study, however a geometric mean in the 2001 study (Jegadeesh & Titman, 2001). Theoretically the arithmetic mean has an upward bias, while the geometric mean has a downward bias. The key difference between arithmetic and geometric means lies in the treatment of negative returns. For example, if investors lose 100 percent of their initial investment, how does this affect the accumulated profit? Given for example that the return of the previous two periods were 100 percent, an arithmetic mean would postulate that the investors had accumulated 33.33 percent. The geometric mean on the other hand would postulate that the investors had lost all the accumulated profit. This way, investors should be more concerned about the geometric mean, rather than the arithmetic mean as they are displaying historical returns. The calculation of the arithmetic and geometric means can be found in chapter 7.

Lastly, the definition of statistical significance of the regressed returns is additionally a highly important model specification. The chosen significance test is the standard Welch test statistic that is based on the assumption that two populations are not homogeneous distributed (Agresti & Franklin, 2009). As we are interested in positive alpha creation, i.e. returns in excess of zero, we use the test statistics to test the significance of the multi-asset momentum not being equal to zero. We could additionally have tested the significance of the multi-asset momentum not being equal to the population, yet we find the former specification more appropriate. The calculation can be found in chapter 7. We primarily evaluate the test statistics on either a 90 or a 95 percent significance level with the corresponding test statistics of 1.65 and 1.96, respectively (Agresti & Franklin, 2009). We acknowledge that some articles are operating at a 99 significance level (2.58), however we do find the former levels sufficient.

5.2 Returns of Multi-Asset Momentum

5.2.1 Multi-Asset Performance

Chapter 3 illustrated that several published articles during the past 20 years have indicated that momentum is profitable up to a 12 month period in each of the four distinct broad asset classes. Chapter 1 and especially section 1.1 motivated the potential of combining the four broad asset classes to verify whether a multi-asset approach in fact would capture the underlying momentum effect of the asset classes. Table 5.1 reports the evidence from applying the 1993 Jegadeesh and Titman methodology, longing the best performing quartiles and shorting the worst. We are applying five formation and holding periods to capture the short run momentum effects.

Table 5.1 illustrates that all zero-cost multi-asset long-short trading strategies indicate strong annualised momentum that furthermore are strongly significant in the whole sample period. The benchmark portfolio that was formed on six month prices and held subsequently six months, produces a significant annualised excess return of 9.19 (3.11) percent, which is approximately identical to the findings in table 3.4. Especially the equity markets have similar performance (Jegadeesh & Titman, 1993; Nijman et al., 2004). The most significant performance is generated in a portfolio based on six months past prices and held for subsequently one year. With an annualised long-short performance of 18.31 (6.80) percent it has approximately outperformed the reminders by 80 percentage points. Furthermore the portfolio based on the past years prices and held for three months (Jegadeesh & Titman, 1993; Lui et al., 1999), had a significant long-short performance of 10.49 (4.39) percent. Table 5.1 illustrates the significant potentials for investors to combine four broad asset classes and cross-sectionally select the best and worst performing asset classes in the sample period December-1999 to December-2011.

Table 5.1: **Absolute Performance of the Multi-Asset Momentum strategies**

Table 5.1 establishes the evidence for 25 multi-asset momentum strategies that are formed on *J months* lagged returns and held for subsequently *K months*. The values of the parameters *J* and *K* for the different trading strategies are indicated in the first column and row, respectively. The t-statistics are reported in brackets. The sample period is December 1999 to December 2011.

		Holding Period (K)				
Formation Periods (J)	**Portfolio**	**1**	**3**	**6**	**9**	**12**
1	Top Quartile (%)	5.77	4.65	6.82	6.62	5.83
	Bottom Quartile (%)	-10.12	-7.29	-4.92	-6.61	-5.69
	Long-Short (%)	15.90	11.94	11.74	13.24	11.53
		(6.09)	(4.87)	(5.03)	(5.95)	(5.29)
3	Top Quartile (%)	5.39	5.49	6.27	5.74	4.76
	Bottom Quartile (%)	-2.20	-3.80	-4.73	-4.29	-5.72
	Long-Short (%)	7.60	9.30	11.00	10.03	10.49
		(*1.83)	(2.96)	(4.23)	(3.96)	(4.35)
6	Top Quartile (%)	8.30	12.14	3.69	5.24	5.31
	Bottom Quartile (%)	-6.07	-6.07	-5.49	-6.29	-5.77
	Long-Short (%)	14.38	18.22	9.19	11.53	11.08
		(4.11)	(5.37)	(3.11)	(4.32)	(4.66)
9	Top Quartile (%)	3.59	0.01	-0.33	2.10	2.93
	Bottom Quartile (%)	-4.72	-7.46	-11.80	-9.13	-8.80
	Long-Short (%)	8.31	7.48	11.47	11.23	11.73
		(2.66)	**(*1.71)**	(4.26)	(3.65)	(3.96)
12	Top Quartile (%)	5.72	6.34	7.24	5.46	5.74
	Bottom Quartile (%)	-2.91	-3.02	-11.07	-3.07	-5.54
	Long-Short (%)	8.63	9.37	18.31	8.54	11.29
		(2.91)	(2.62)	(6.80)	(2.36)	(3.92)

**Insignificant at the 95 percent significance level*

One possible cause of the significance in table 5.1 can be explained by table 5.2 which illustrates the momentum in each of the four broad asset classes. As our applied methodology corresponds to the articles from table 3.4, we expect the evidence from table 5.2 to resemble the previous literature.

Panel A and B reports essentially the same numbers as table 5.1 as Panel A reports the multi-asset long-short performance given various formation periods J and holding periods K. Panel B is the significance of the long-short performance. Panel C, D, E and F reports the significance of an equity, debt, commodity and currency sample from the initial multi-asset data sample, respectively. The long-short performance for the four broad asset classes is less important, than the significance, as we will use table 5.2 to explain the underlying drivers of the multi-asset momentum.

Panel C exhibits that the equity asset class has significant long-short performance in the sample period, with exemptions of the nine month formation period with subsequent holding periods above six months. This finding support the argument, that momentum in equities is a short term state and will dilute in the long run. With respect to previous academic studies the significance level corresponds to the t-statistics from table 3.4. The average t-statistics for equity markets was close to four which corresponds to the t-statistics of table 5.2. As the previous equity momentum literature highlighted, the strongest and most significant momentum evidence is located in the square with formation and holding periods of one, three and six months, which can be supported by panel C in table 5.2.

Panel D illustrates the significance of a carve out of the included fixed income indices that have had the best absolute performance in the sample period. Given this fact, the debt asset class is assumed to exhibit the strongest significance as well. This is also the case, as panel D exhibits the most significant long-short performance in the sample period. All combinations of portfolio composition in the debt carve out produces higher significance than any of the reminder portfolio combinations in panel C, E and F. The strongest significance is based on one month past prices that held subsequently 1, 3, 6, 9, 12 months. The evidence from panel D does not support previous evidence (Gebhardt et al., 2005) from table 3.4 as they found significant underperformance on long-short corporate bonds of -1.44 percent (-2.59). However, panel D does support Jostova et al. (2010) that found highly significant excess performance in predominantly the high-yield segment of 1.92 (8.72) percent. As (Gebhardt et al., 2005) applied a complete different sample period, we do not regard their findings crucial for our analysis. The significance reported in (Jostova et al., 2010) was, in addition to this thesis, based on a much narrower data sample with a less diverse bond selection approach. Despite this fact, the t-statistics found in both panel D as well as (Jostova et al., 2010) have remarkable similar significance of 8.97. Given the strong performance, as well as the significant long-short performance of the debt asset class, indicates that in the sample period December 1999 to December 2011, such assets could potentially have driven some of the multi-asset momentum in table 5.1.

Panel E reports the significance of the commodity carve out. One important feature of the commodity sample is *"that commodities potentially can be trading with either a shortage or an oversupply that would generate highly volatile prices"* (Wind, 2012). On the one hand, an example of oversupply could happen as a consequence of advantageous conditions for agricultural corn production. If the weather conditions has been unusually well the past season and farmers are fully able to meet the demand for corn, any excess supply will trigger the overall corn prices to decrease rapidly, as the news becomes available in the market. On the other hand, an example of shortage could happen as a consequence of insufficient foreign supply of oil. If the oil producing countries are not shipping sufficient oil to match the demand, the price of crude oil will increase rapidly, as the news becomes available in the market. This way, a trade embargo could potentially mean that commodity prices would either increase or decrease disadvantageously to consumers, but advantageously to momentum investors. Due to the fact that commodity are relying on factors that investors by no means have the opportunity to influence e.g. the climate or foreign governments, the commodity asset class as well as the underlying single commodities are assumed to be the most volatile (and risky) asset class to invest in. As panel E reports 80 percent of the various portfolio combinations are significant which is supported by table 3.4. The average t-statistics is around three, which furthermore applies in especially (Shen et al., 2007) with 4.87 and (Miffre & Rallis, 2007) with 2.47. Panel E indicates that commodities could potentially be positively affecting the multi-asset momentum in a combination with the debt asset-class. Previous findings supported this argument and added that commodity momentum solely was profitable in the short run as it vanished in the long run (Moskowitz et al., 2012).

Panel F reports the significance of a carve out from the initial data sample in eight various exchange rates. As chapter 4 postulated, investing in the currency markets will in the long term by a zero-sum game due to the unorganised exchange market as well as the highly capitalised traders at the investment banks. This way, private investors will not stand much chance in such markets, hence their losses will be the professional traders gain (Sercu, 2009). This way, we assume that investing in exchange rates should be the most efficient market, hence the significance is expected to be low or even negative as investors should not be able to exploit inefficiencies in the currency markets. Panel F support this assumption, yet the significance is extremely varicoloured. 44 percent of the portfolio combinations does not have significant alpha and 28 percent are in fact negative (16 percent are significantly negative). The only approximate pattern is located at portfolios that are based on three months past prices and held in excess of three months. This indicates that the currency momentum, if any at all, is limited to an short term period. Above three months formation periods the significance vanishes or becomes negatives in 73 percent of the portfolio combinations. The results for panel F does not however support the previous findings from table 3.4, but does support the previous findings of (Moskowitz et al., 2012) that found the currency market to be highly efficient as well. We find it striking that (Serban, 2010), who has applied approximately there same sample size as well as sample period has excess performance of 11.2 percent, which is one of the highest in table 3.4. As the significance level is not reported we do not regard this study as an accurate benchmark of panel F. (Okunev & White, 2003) uses a different methodology and (Menkhoff et al., 2012) apply a much larger sample size, hence we do not regard such studies as an accurate benchmark neither. Given the low or negative significance, we does not see the currency asset class as neither a catalyst nor accelerator of multi-asset performance.

Table 5.2: **Multi-Asset and Asset Class Significance**

Table 5.2 establishes the alpha significance for 25 multi-asset momentum portfolios as well as 100 asset class specific momentum strategies. Panel A and B report the multi-asset alpha and significance, respectively. Panel C, D, E and F are carve outs from the multi-asset sample based on equity, debt, commodities and currency, respectively. The sample period is December 1999 to December 2011.

(J,K)	**A**	**1**	**3**	**6**	**9**	**12**	**B**	**1**	**3**	**6**	**9**	**12**
1		15.90	11.94	11.74	13.24	11.53		6.09	4.87	5.03	5.95	5.29
3		7.60	9.30	11.00	10.03	10.49		***1.83**	2.96	4.23	3.96	4.35
6		14.38	18.22	9.19	11.53	11.08		4.11	5.37	3.11	4.32	4.66
9		8.31	7.48	11.47	11.23	11.73		2.66	***1.71**	4.26	3.65	3.96
12		8.63	9.37	18.31	8.54	11.29		2.91	2.62	6.80	2.36	3.92
(J,K)	**C**	**1**	**3**	**6**	**9**	**12**	**D**	**1**	**3**	**6**	**9**	**12**
1		4.29	3.34	2.99	2.41	2.76		15.38	11.77	12.52	13.58	12.10
3		2.98	3.15	2.74	2.12	***1.61**		11.72	8.35	10.85	10.03	4.92
6		2.53	4.20	4.20	2.71	2.65		8.97	8.86	3.21	4.94	8.14
9		2.62	2.38	***1.40**	***0.86**	***1.63**		10.80	8.94	8.62	11.91	11.74
12		3.30	2.08	3.72	3.30	2.92		10.78	8.63	9.80	9.15	6.21
(J,K)	**E**	**1**	**3**	**6**	**9**	**12**	**F**	**1**	**3**	**6**	**9**	**12**
1		3.15	2.59	5.47	2.73	4.22		***-0.78**	***0.63**	3.72	2.25	***0.09**
3		2.21	***1.32**	***0.55**	7.64	5.15		***0.79**	2.18	2.75	4.90	3.97
6		2.02	2.66	2.60	3.37	2.50		4.46	***-0.30**	***-0.52**	***1.33**	****-2.97**
9		2.15	***0.27**	***1.41**	3.56	3.02		2.26	***1.57**	****-3.23**	****-3.56**	****-3.43**
12		2.73	4.44	3.91	***1.62**	3.57		***1.44**	***0.63**	3.08	***1.74**	2.28

**Insignificant at the 95 percent significance level*

***Significant, yet negative alpha estimates*

The multi-asset dependence to both equities and commodities can additionally be illustrated in figure 5.3 that illustrates the correlation structure between the multi-asset momentum strategy and the four broad asset classes. Both the equity and the commodity asset classes have positive correlation of 0.59 and 0.81, respectively compared to the currency asset class that have a correlation of 0.43. Figure 5.3 support the evidence that the multi-asset momentum strategy is highly related to the underlying equity and commodity indices as well a the beneficial correlation structure between equity and commodity.

Table 5.3: **Multi-Asset Correlation Structure**

Table 5.3 illustrates the correlation structure of the cross-sectionally pooled four broad asset classes on the multi-asset momentum. We use the notation in the first row as follows: EQT=Equity, DBT=Debt, COM=Commodity, FXC=Currency and MUL=Multi-Asset. The sample period is December 1999 to December 2011.

	EQT	**DBT**	**COM**	**FXC**	**MUL**
Equity	1.000				
Debt	0.693	1.000			
Commodity	**0.077**	0.144	1.000		
Currency	0.602	0.796	0.116	1.000	
Multi-Asset	**0.587**	0.514	**0.811**	**0.435**	1.000

5.2.2 Long-Short Subsets

We have learnt from section 5.2, including table 5.1 and table 5.2 that momentum is significant and strong in especially the debt segment and can easily be associated with the underlying momentum in equities and commodities as well. The only asset class not fully reflected a strong significance was the currency segment, hence indicating that this asset class is relatively more efficient than the three remaining. The scope of this thesis was to investigate the potential of multi-asset momentum, i.e. if investors could cross-sectionally compose alpha generating portfolios. Especially table 5.1 and table 5.2 illustrated that such strategy was profitable up to a 12 month basis. We extend the knowledge from section 5.2 to table 5.4 to only include a subset of five portfolios from the initial 25 multi-asset zero-cost portfolios. These subsets are selected arbitrarily, yet they all have the feature of having the same formation and holding periods, respectively. This way, the five subset portfolios are the diagonal from table 5.1, starting at portfolio 1-1 and ending in portfolio 12-12. Along this diagonal, the benchmark portfolio, the six month formation and six month holding, is located as well. In addition to table 5.1, table 5.4 reports a deeper insight in the actual performance of the multi-asset zero-cost trading strategies. Where table 5.1 only reported the alphas and significance, table 5.4 will elaborate more on the origin of the alphas as well as include four important measures of relative performance and risk. With point of reference to the benchmark portfolio, the four quartiles are reported in the upper row.

The *Q1* represent the best performing asset classes and *Q4* represent the worst performing asset classes. The *Q2 and Q3* represent the residual asset classes that do not perform in either Q1 or Q4. The risk is the *annualised volatility* of the four portfolios and the *sharpe* ratio is the risk adjusted performance measure. Investors would want to increase their sharpe ratios to ensure the highest return relative to the associate risk. The alpha is the performance from longing the best performing asset classes Q1 and shorting the worst performing asset classes Q4. The *tracking error* is the deviation from an long-only equally weighted strategy in all 50 asset classes. Active investors want to maintain high tracking errors, where passive investors want to limit their tracking errors. Investors cannot universally define the most appropriate tracking error, thus investors predominantly apply the tracking error estimate as a part of the relative alpha measure. Such relative measure is named the *information ratio*, and is calculated as alpha relative to the tracking error. Like the desirable high sharpe ratio, a high information ratio is additionally preferred by the investors. If investors are maximising the information ratio this would imply that the excess return generated is not based on high deviations from the benchmark (in this thesis an equally weighted multi-asset portfolio). This way, investors remain true to the benchmark, which, ceteris paribus, would be more desirable than an equivalent high excess return with much higher risk than the benchmarks. As a rule of thumb, information ratios in excess of one indicate that the investors have generated beneficiary excess returns.

With regard to the benchmark portfolio, table 5.4 illustrate a tendency to that the multi-asset momentum is driven by the worst performing quartiles. The absolute performance of Q4 is -5.4 percent which is higher than the Q1 performance of 3.69 percent. The same is present in the portfolio 1-1 and the portfolio 9-9 i.e. 60 percent of the subset portfolios in table 5.4.

Table 5.4: **Relative Performance of the Multi-Asset Momentum strategies**

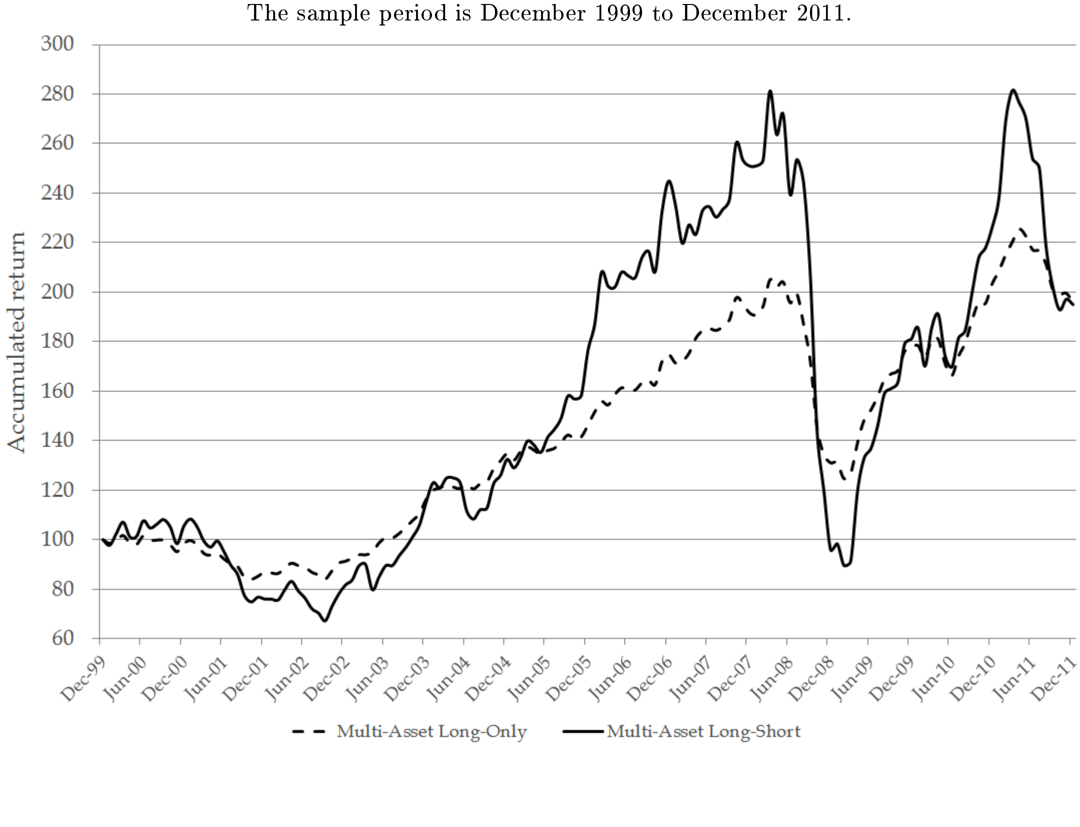
Table 5.4 establishes the risk-return relationship of five portfolio subsets. The alpha is the long-short profit of the multi-asset momentum strategy. The applied risk-free rate is the three-month US Treasury bill and the benchmark is a long-only equally weighted strategy in the 50 asset classes. The significance is reported in brackets. The sample period is December 1999 to December 2011.

	Q1	**Q2**	**Q3**	**Q4**		**Q1-Q4**
Portfolio 1-1					Alpha (%)	15.90
Return (%)	5.77	4.71	6.82	-10.12	t-stat	(6.09)
Risk (%)	14.66	12.66	15.63	17.11	Tracking Error (%)	3.71
Sharpe Ratio	0.24	0.19	0.29	-0.72	Information Ratio	4.27
Portfolio 3-3					Alpha (%)	9.30
Return (%)	5.49	5.96	0.21	-3.80	t-stat	(2.96)
Risk (%)	13.73	15.58	8.61	15.53	Tracking Error (%)	3.31
Sharpe Ratio	0.23	0.23	-0.23	-0.38	Information Ratio	2.80
Portfolio 6-6					Alpha (%)	9.19
Return (%)	3.69	4.71	-6.36	-5.49	t-stat	(3.11)
Risk (%)	14.24	12.33	15.38	14.39	Tracking Error (%)	3.54
Sharpe Ratio	0.10	0.19	-0.55	-0.53	Information Ratio	2.59
Portfolio 9-9					Alpha (%)	11.23
Return (%)	2.10	3.44	-1.78	-9.13	t-stat	(3.65)
Risk (%)	15.53	14.08	4.36	16.03	Tracking Error (%)	2.93
Sharpe Ratio	-0.00	0.08	-0.91	-0.70	Information Ratio	3.82
Portfolio 12-12					Alpha (%)	11.29
Return (%)	5.74	4.72	2.8	-5.54	t-stat	(3.92)
Risk (%)	14.99	14.37	11.13	14.64	Tracking Error (%)	4.96
Sharpe Ratio	0.23	0.17	0.05	-0.53	Information Ratio	2.27

The Q4 performance is additionally more volatile than the Q1 performance, which is expected due to the dispersion in returns. The same is evident in portfolio 1-1, 3-3 and portfolio 9-9 i.e. 80 percent of the subset portfolios in table 5.4. This indicates that worst performing asset classes are, to some extent, driving the momentum in the multi-asset portfolio due to a higher inherent risk in Q4. This can furthermore be seen in the higher absolute sharpe ratios of the Q4 portfolios. Due to this fact, the sharpe ratios are higher in every case of Q4 relative to Q1. The alphas from longing Q1 and shorting Q4 are positive and significant in either case. The benchmark portfolio produces an annualised alpha of 9.19 (3.10) percent. The alphas are evident in the entire subset portfolios - also indicated in table 5.1. The entire subset is deviating moderately from the long-only equally weighted strategy across the 50 asset classes, why the tracking error of the benchmark portfolio is 3.54 percent. Concatenating the alpha and the tracking error, the information ratio is larger than one in all of the subset, which indicates that the alpha creation is not biased by high deviations from the equally-weighted positions in each of the 50 asset classes. The information ratio is largest in the portfolio that is based on one month past prices and held for subsequently one month with 4.28 percent and lowest in the portfolio that is based on 12 month past prices and held for subsequently 12 months with 2.27 percent. This support the previous findings of short run profitability. The average information ratio in the entire subset is 3.15 percent which supports the idea that the produced zero-cost trading alpha is not due to deviation from the equally weighted investment across all asset classes. If this was not the case, we would postulate that investors would be better of allocating 2 percent in each of the 50 asset classes (or even refrain from investing across assets). The significant performance of the long-short momentum portfolio compared to the long-only strategy across the 50 asset classes is furthermore illustrated in figure 5.1. The multi-asset long-only strategy is significantly outperformed by the multi-asset long-short strategy.

Figure 5.1: **Multi-Asset Long-Short versus Multi-Asset Long-Only**

Figure 5.1[11] illustrates the long-only multi-asset momentum versus the long-short multi-asset momentum. The sample period is December 1999 to December 2011.



To support the evidence from table 5.2, the profits from table 5.1 and the results of table 5.4 we assess the 50 asset class on the basis of their inclusion in the four quartiles following the applied methodology. This is done in panel A and panel B of figure 7.3.

Figure A illustrates the distribution of the individual asset classes included in either Q1, Q2, Q3 or Q4. If an asset class has performed sufficiently well to be held in the best performing quartile, Q1, e.g. 10 per cent of the time in the sample period, such asset class would have a bar height of 10 in figure 7.3. As we, according to the applied methodology, is long in Q1 and short in Q4 and given that momentum strategies perform their best in extreme environments, the optimal portfolio combination that yields the highest alpha, would, ceteris paribus, be composed by extremely well performing asset classes combined with extremely bad performing asset classes. Figure 7.3 support the previous findings of strong Q1 performance in both emerging equities and commodities, yet their inclusion in Q4 is not easy to detect in figure A. Thus, we included figure B.

Figure B is ranking the performance of the 50 underlying asset classes in both Q1 and Q4 where we want to rank the asset classes included the most frequently in both Q1 as well as Q4. The best performing asset class in Q1, i.e. the asset class included most frequently in Q1, is allocated 50 points, the second best 49 points, third best 48 points etc. Consequently the best performing asset class in Q4, i.e. the asset class least frequently included in Q4, is allocated 1point, the second 2 points, the third best 3 points etc. The maximum score thus is 100 points, given that an asset class is both allocated 50 point is both Q1 and Q4, respectively. As stated in section 5.2, especially commodities have the potential of being the most volatile broad asset class due to the inherent potentials of shortage and excess supply in the traded contracts, thus we expect commodities to have a high ranking. Currencies are expected to be an approximate zero-sum game, hence we do not expect a high ranking in currencies. Equities and debt are both financial assets and given table 5.2, we expect both asset classes to rank above average. As panel B illustrates, our assumptions are to some extent fulfilled, as 18 of the 20 highest ranked are commodities. This was furthermore expected from table 4.1.

Gold and cattle are the only two commodities not ranked among the 20 highest rankings. Gold is not as volatile as the remainder of the commodities as gold is ranked 26 in Q4 and 27 in Q1, and is given a total score of 53. The same apply for cattle which ranks 32 i Q4 and 14 in Q1 with a total score of 46. Neither gold nor cattle display volatile behaviour, which can be explained by a healthy supply and demand relationship supported by figure 4.1. Following the volatile commodities, the emerging market equity indies emerge. The core, growth and value indices are ranked between a total score 69 and 55, i.e. above the average. This can be explained by the higher risk in the emerging market countries. In the lowest part of the ranking we have a mixture of currencies, equity and debt indices mainly centred around the US and Europe. This can be explained by the more stable environments in the most developed part of the world both financially and governmentally, hence such indices form an infrequent part of the Q1 or Q4. Figure B supports the fact from both table 5.2 and table 5.1 that postulated strong long-short potential in commodities, equities and bonds which align by the total ranking of the aggregate score between Q1 and Q4.

5.3 Alpha Explanations

5.3.1 Internal Impacts

Before turning to table 5.5 and table 5.6, we have to elaborate on a vital assumption in relation to the explanatory power of the alpha and beta estimates from the applied factor model. Any momentum evidence in the sample period is by definition neither static nor an isolated event, but rather the outcome of several diverse events across time. Explaining momentum using factor models can potentially have the downside that investors could miss out crucial factors, such that the origin of the momentum will remain unexplained. This in mind, we will in this section, test for up to six internal factors, that potentially could outline the basics of the momentum existence. The results of this section will be related to the results of (Blitz & Vliet, 2008). We run two step-wise regressions that consecutively loads on more factors. We will name the beta estimates factor loadings as they symbolises sensitivity to momentum. Positive factor loadings will contribute positively to the momentum in addition to negative factor loadings that contributes negatively.

The overall regression, which includes all the internal impacts, can be estimated using equation 5.1:

$$
\begin{aligned}
r_{J,K}^{MOM} = \alpha \quad &+ \quad \beta_{MKT}MKT + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{UMD}UMD \\
&+ \quad \beta_{BOND}BOND + \beta_{DJUBS}DJUBS
\end{aligned}
\tag{5.1}
$$

where α is the return unexplained by the model parameters. The results from SAS 9.2 is illustrated in table 5.5, where MKT = MSCI World, SMB = the Fama-French size factor, HML = the Fama-French style factor and UMD = the Charhart momentum factor. DJUBS = the Dow Jones UBS commodity index and should capture the expected strong bias towards commodities the same way as the bond factor where BOND = Barclays Global Aggregate. Table 5.5 report the model estimates of the benchmark portfolio as well as the average factor loadings across all 25 portfolio combinations.

Table 5.5: **Alpha Explanations - Internal Impacts**

Table 5.5, Panel A, report the factor loading to the benchmark portfolio. Panel B report the factor loading across the 25 multi-asset momentum portfolios. The t-statistics are reported in brackets and are based on the model estimates. The alpha estimates have been multiplied by 100 and the R^2 is the adjusted measure. The sample period is December 1999 to December 2011.

Panel A	**Intercept**	**MKT**	**HML**	**SMB**	**UMD**	**BOND**	**DJUBS**	R^2
Market Bias	1.28	0.77						*0.25*
	(2.38)	**(*4.43)**						
Style and Size Bias	1.22	0.78	-0.01	0.10				*0.24*
	(2.21)	**(*4.41)**	**(-0.08)**	(0.61)				
Momentum Bias	1.20	0.80	0.00	0.13	0.82			*0.25*
	(2.15)	**(*4.61)**	(0.01)	(0.73)	(0.84)			
Index Bias	0.84	0.78	-0.11	-0.05	0.38	0.17	0.91	*0.66*
	(2.09)	**(*8.75)**	**(-1.12)**	**(-0.53)**	(0.63)	(0.77)	**(*11.10)**	
Panel B	**Intercept**	**MKT**	**HML**	**SMB**	**UMD**	**BOND**	**DJUBS**	R^2
Market Bias	0.92	0.69						*0.23*
	(1.73)	**(*4.68)**						
Style and Size Bias	0.80	0.69	0.07	0.16				*0.23*
	(1.43)	**(*4.67)**	(0.58)	(0.98)				
Momentum Bias	0.79	0.70	0.08	0.17	0.50			*0.22*
	(1.40)	**(*4.75)**	(0.64)	(1.04)	(0.68)			
Index Bias	0.39	0.68	-0.05	-0.02	0.04	0.21	0.96	*0.72*
	(1.12)	**(*9.74)**	**(-0.47)**	**(-0.12)**	(0.20)	(1.37)	**(*15.11)**	

**Significant at the 99 percent significance level*

Benchmark Portfolio Panel A in table 5.5 regress the excess return of the benchmark portfolio on the returns of MSCI World. In this case, the benchmark portfolio delivers large and significant alpha with respect to the market factor of 1.28 (2.38) per month. The portfolio further loads significant and positive on the market factor by 0.77 (4.43). Adding both the style and size biases to the model, the alpha remains significant and positive of 1.22 (2.21), yet slightly reduced. The market factors is stable at 0.78 (4.41), yet the benchmark portfolio does not load significantly on neither the small cap bias (0.61) nor the value bias (-0.08).

Adding the momentum factor to the model the alpha is further reduced to 1.20 (2.15), yet remaining significant. The market factor remains stable at 0.80 (4.61). None of the three additional factors are significant, and it appears that neither the small cap bias, value bias nor the cross-sectional momentum bias positively affect the multi-asset momentum. Finally, adding the bond and the commodity index to the model reduces the alpha even more, yet it does not affect the significance of the alpha estimate.

The significance of the market factor increases further, but neither the style, the size, the momentum nor the bond biases are significant. However the commodity factor loading is high and significant at 0.91 (11.10) and indicates that the broad commodity factors does explain part of the multi-asset momentum.

Average Portfolio The significance patterns from panel A in table 5.5 can furthermore be traced in the panel B of table 5.5 that reports the average of all the 25 multi-asset momentum portfolios. The market factor as well as the commodity factor remain highly significant and positive, yet the average alpha delivered by the 25 portfolio is not significant. In fact, the average alpha almost vanishes as all the six factors are included. The findings suggests, as stated in the beginning of section 5.3 that not every portfolio is biased from the same factors at all times. Thus on average, the market factor as well as the commodity factors do in fact significantly explain some of the excess momentum returns. The same conclusions was drawn from (Moskowitz et al., 2012) that found similar factorial patterns as well as moderate R^2 of 0.24. We can deduce from the results that the commodity factor as well as the market factor does explain part of the variation of the multi-asset momentum, however still a significant part of the variation is left unexplained. Due to this fact, we introduce four additional factors in the next section.

5.3.2 External Impact

Following the methodology of table 5.5, we swap the four insignificant internal model variables with four external variables, thus maintaining the commodity and the market factors. We include two risk biases as the VIX and the TED-spread. The **VIX** measures the implied volatility of S&P500 options and is often referred to as the *fear index* as is represent the market's expectations to the equity market volatility over the next 30 days. For example, given a VIX of 15 the market expects an annualised change in the equity market over next 30 days of 15 percent, i.e. close to 4 percent during the next 30 days. A high VIX does not necessarily mean bearish outlook for equites, but rather that investors expects the market to move sharply, whether downwards or upwards, within the next 30 days. This could potentially benefit the multi-asset portfolios. The **TED-spread** is a measure of the perceived credit risk in the economy. The TED-spread is measures as the difference between the three-month LIBOR rate (previously relative to Eurodollar contracts) and the three-month US Treasury bill (Sercu, 2009). As the the LIBOR rate can be interpreted as the credit risk of lending to commercial banks and the US Treasury bill can be interpreted as risk-free rate, an increase in the TED-spread will indicate that the lenders expects the risk of defaults on interbank loans to be increasing. Lenders will demand a higher interbank rate or accept a lower risk free rate which can be translated as an increase in the commercial credit risk. The **CPI** is the consumer price index can be interpreted as a measure of inflation. An increasing CPI, indicates higher prices, hence higher inflation. The last variable is the Newedge **CTA** index which is the leading benchmark for trend following strategies. It is calculated based on a subset of managed futures such as Barclay Agricultural Traders, Barclay Currency Traders etc.

Table 5.6: **Alpha Explanations - External Impacts**

Table 5.6, Panel A report the factor loading to the benchmark portfolio. Panel B report the factor loading across the 25 multi-asset momentum portfolios. The t-statistics are reported in brackets and are based on the model estimates. The alpha estimates have been multiplied by 100 and the R^2 is the adjusted measure. The sample period is December 1999 to December 2011.

Panel A	**Intercept**	**MKT**	**DJUBS**	**TED**	**VIX**	**CPI**	**CTA**	R^2
Market Bias	0.51	0.71	0.93					*0.82*
	(2.18)	**(*12.3)**	(2.05)					
Risk Biases	0.61	0.72	0.93	-0.22	-0.12			*0.82*
	(2.40)	**(*8.66)**	(2.02)	(-1.03)	**(-4.76)**			
Macro Biases	0.83	0.74	0.94	-0.25	-0.11	-0.65	-0.11	*0.82*
	(*2.75)	**(*9.73)**	(2.01)	(-1.18)	**(-4.61)**	(-1.57)	(-1.30)	
Panel B	**Intercept**	**MKT**	**DJUBS**	**TED**	**VIX**	**CPI**	**CTA**	R^2
Market Bias	0.45	0.68	0.60					*0.72*
	(*2.69)	**(*7.15)**	(1.88)					
Risk Biases	0.58	0.70	0.83	-0.25	-0.11			*0.72*
	(1.80)	**(*4.44)**	**(*3.02)**	(-1.13)	**(-4.17)**			
Macro Biases	0.76	0.72	0.95	-0.48	-0.11	-0.63	-0.03	*0.72*
	(2.12)	**(*4.44)**	**(*3.06)**	**(-2.41)**	**(-4.14)**	(-1.79)	(-1.44)	

**Significant at the 99 percent significance level*

The overall regression, that includes all the external impacts, can be estimated using equation 5.2:

$$\begin{aligned} r_{J,K}^{MOM} = \alpha \quad &+ \quad \beta_{MKT}MKT + \beta_{DJUBS}DJUBS + \beta_{TED}TED + \beta_{VIX}VIX \\ &+ \quad \beta_{CPI}CPI + \beta_{CTA}CTA \end{aligned} \tag{5.2}$$

where α is the return unexplained by the model parameters. The results from SAS 9.2 is illustrated in table 5.6, where MKT = MSCI World, DJUBS = the Dow Jones UBS commodity index, TED = the TED-Spread, VIX = the VIX index, CPI = the inflation and CTA = the Newedge Commodity Trading Advisor index. Table 5.6 report the model estimates of the benchmark portfolio as well as the average factor loadings across all 25 portfolio combinations.

Benchmark Portfolio The first regression of the first panel in table 5.6 regresses the excess return of the benchmark portfolio on the returns of MSCI World and the broad commodity index. Both indices were highly significant in table 5.5, hence we maintain both indices in this model. In this case, the benchmark portfolio delivers large and significant alpha. The portfolio loads significantly and positively on the market factor by 0.71(12.31) as well as the commodity factor 0.93 (2.05). This is aligned with table 5.5. Adding both the VIX-factor and the TED-spread to the model, the alpha remains significant and positive of 0.61 (2.40). The market factor is stable at 0.72 (8.66) as well as the commodity factor at 0.93 (2.02). The benchmark portfolio does not load significantly on neither the TED-spread (-1.03), but does load negatively, yet significant on the VIX (-4.61). This indicate that an increase in the VIX by one unit will negatively affect the multi-asset momentum. We thus find that multi-asset momentum returns are larger following a positive market with low perceived future volatility. Adding the CPI and the CTA to the model, the alpha is further increased to 0.83 (2.75). The market factor reminds stable at 0.74 (9.73) as well as the commodity factor at 0.94 (2.01). The TED-spread remains insignificant (-1.18) while the VIX remains negative, yet significant (-4.61). Neither the CPI nor the CTA is significant and load negatively on the benchmark portfolio.

Average Portfolio The average portfolio draws the same conclusions as the benchmark portfolio. However, one crucial point is, that the TED-spread, in case of including all six variables, becomes significant (-2.41). It seems, on average that the TED-spread is in fact able to significantly explain some of the average produced alpha. In the average approach, it is important to notice that the significance of the VIX is on the same level as the market factor. The postulate from the previous paragraph can thus be supported as high positive momentum along with low expected volatility significantly drives the multi-asset momentum. Furthermore the R^2 is high in each of the six regressions at 0.82 and 0.72, respectively. This indicates that the model does explain a large part of the variation in the model.

5.4 Out of Sample Performance

One argument that can easily be justified is that momentum can be related to given periods in time, hence momentum strategies work better in some periods than others (Marekwica, 2011). Table 5.7 illustrates five consecutive periods from the inception of the momentum strategy in December 1999 to the end of December 2011. The periods have been assigned arbitrarily, yet the overall intention has been to capture the up- and down markets during the sample period. It illustrates the long-short momentum of the entire sample period of the diagonal portfolios.

The period from the inception of the data sample to end 2002 is represented as the Tech crash as performance in this period was heavily affected by the crash of the overvalued technology equites. The multi-asset momentum in this periods is neither significant nor positive across all portfolios. Both the portfolio 3-3, 9-9 and 12-12 are not profiting on shorting the worst performance deciles and longing the best performers. In fact, such strategies underperform significantly. The 6-6 portfolio has positive long-short performance, yet insignificant. The only portfolio in this period than have significant performance is the shortest termed 1-1 portfolio. The period from the beginning of 2003 to the end of 2007 represents the rebound period and has strong and significant multi-asset performance indicating that multi-asset zero-cost strategies could be benefitting from increasing equity markets as was also evident in table 5.5 and table 5.6. The subsequently one year crash of the financial markets in 2008 thus eroded the performance of the multi-asset strategy in all five portfolio combinations. In this period, investors could not expect the performance of the best performing asset class to continue (in fact the performance indicates the opposite). The period from the crash in 2008 until the end of the sample-period exhibits strong and significant performance, which is aligned with the previous rebound period following the Tech crash. Table 5.7 support the previous section in the fact that positive markets significantly drives the multi-asset momentum. Both the Tech cars as well as the credit crash indicated inferior multi-asset performance that was restored by in the rebound periods. These finding was additionally evident in figure 5.1 that illustrated show the multi-asset momentum strategy performed during the sample period.

Additionally, during the entire sample period, investors have gone through two cycles. The first cycle was initiated at the peak of the Tech bubble until the beginning of the credit crash. The second cycle was initiated at the beginning of the credit crash until the end of the data sample (approximately). It is evident that the performance of the multi-asset portfolios have been far better in the first cycle, where the entire subsets experience large and significant alpha. In the second cycle, only the 1-1 and the 9-9 portfolio have significant long-short performance. Despite this fact, the performance of the second cycle has to be taken with a grain of salt, as the cycle have not fully recovered at the point of publication of this thesis. This support the introductory remark, that *momentum can be related to given periods in time*. On the one hand, given that the data sample was solely based on the first cycle, we could have inferred that momentum was highly significant and profitable. On the other hand, given that the data sample was based on the second cycle, we could have inferred that was a highly disadvantageous investment strategy.

Table 5.7: **Out of Sample Performance**

Table 5.7 establishes the evidence for five out of sample multi-asset momentum strategies that are formed on *J months* lagged returns and held for subsequently *K months*. The values of the parameters *J* and *K* for the different trading strategies are indicated in the first column, while the seven various time periods are reported in the first row. The sample period is December 1999 to December 2011.

		Portfolio Selection (J,K)				
Time Period	**Portfolio**	**1-1**	**3-3**	**6-6**	**9-9**	**12-12**
Dec-99 to Dec-11	Long-Short (%)	15.90	9.30	9.19	11.23	11.29
Sample Period	Risk (%)	25.94	24.65	24.53	26.74	25.48
		(6.09)	(4.87)	(5.03)	(5.95)	(5.29)
Dec-99 to Dec-02	Long-Short (%)	7.06	-12.72	1.36	-7.08	-10.60
Tech-crash	Risk (%)	20.64	19.64	16.96	19.61	19.00
		(2.05)	**(*-3.88)**	**(**0.48)**	**(*-2.16)**	**(*-3.34)**
Jan-03 to Dec-07	Long-Short (%)	23.22	30.15	21.82	21.69	32.75
Rebound	Risk (%)	18.69	19.92	18.88	16.64	18.83
		(9.62)	(11.72)	(8.95)	(10.09)	(13.46)
Dec-07 to Dec-08	Long-Short (%)	-64.34	-71.09	-69.39	-69.94	-77.15
Credit-crash	Risk (%)	47.90	44.24	51.27	56.66	53.02
		(*-4.65)	**(*-5.56)**	**(*-4.68)**	**(*-4.27)**	**(*-5.04)**
Dec-08 to Dec-11	Long-Short (%)	35.64	29.15	22.22	48.20	29.94
Rebound	Risk (%)	30.30	27.05	25.48	30.72	26.61
		(7.05)	(6.46)	(5.23)	(9.41)	(6.75)
Dec-99 to Dec-07	Long-Short (%)	17.14	13.34	13.90	10.17	15.97
Cycle 1	Risk (%)	19.45	19.82	18.18	17.81	18.89
		(8.63)	(6.59)	(7.49)	(5.59)	(8.27)
Dec-07 to Dec-11	Long-Short (%)	13.50	-1.03	0.15	13.30	3.03
Cycle 2	Risk (%)	35.52	32.22	33.82	38.86	35.13
		(2.63)	**(-0.22)**	**(**0.03)**	(2.37)	**(**0.59)**

**Negative beta estimates, yet significant at the 95 percent significance level*

***Insignificant at the 95 percent significance level*

5.5 Practical Issues

The Short Issue First and foremost, investing both in long and short positions could, according to previous studies, impose a natural lag between selling short and buying long. If the cash inflow from the short positions should be able to fund the cash outflow from the long positions, investors need to place the short order before placing the long. Simultaneous long and short trading would impose a lag from the short trade is place to the cash is at the investors deposit. This way, the long position is potentially temporary left unfunded by the short position. The short selling issue is most profound in a single security environment, where investors need to trade a specific security, e.g. equity or commodity that need to be available in the market to buy. In this thesis, we set aside this issue, as the problem is not crucial. We assume that positions can be taken through the highly liquid exchange traded funds as proxy to the indices. *"Futures are often applied in the investment industry to ensure a highly liquid and cost effective market. This was hedge fund managers trading in the multi-asset market, does not find the short issue"* (Wind, 2012). Furthermore, positions are traded through intermediates that additionally ensure high liquidity in the market.

Transactions Cost Issue Transaction cost is furthermore vital in actively managed portfolios and is often the main argument for, why passive investments should outperformance active management in the long run (Sharpe, 1991). More importantly, in the case of short selling, transaction costs and margins can eventually mean that short selling is not profitable in the long run. If an investor should replicate an entire index, e.g. the MSCI World, this would mean that he or she should buy more than 1,600 equities. At a standard trading cost investors would face a serious initial investment. Furthermore, shorting would impose an initial margin between 20 to 60 percent of the total value of the short positions in additional to the commonly fixed fee per short position. Therefore, there are several remarks that can be made towards the profitability of a long-short investment. However, in this thesis, positions are taken through low priced exchange traded funds that are highly correlated to the market. Buying and selling exchange traded funds are cost efficient due to the fact that you would buy the entire index at a low standard rate. *"As multi-asset strategies frequently trade in low priced derivatives and contracts, trend-following investment managers does not see the transaction cost as an issue to the overall portfolio composition"* (Wind, 2012).

5.6 Robustness Test

One final test of the strength of the empirical results can be examined by a robustness test. Numerous test for robustness check exists, yet we find a lagged test most appropriate for the scope of this thesis. As we form and hold portfolios, based on arbitrarily selected time frames, we find it important to lag the formation period up to 11 months to illustrate, how the long-short performance in the sample period changes given the first observation. The first row is labeled zero and represents the performance from table 5.4, table 5.1 as well as table 5.2 and illustrates the unlagged performance. Altering the first period by one (lag), the inception data will be January 2000 instead of December 1999. This is the only change in the momentum model, hence we assume that the performance of the multi-asset portfolio should not be altered from the zero lagged performance. As we lag the zero-cost trading strategies up to 11 months, we run the momentum model in each distinct lag, to capture the long-short performance. As the range measure exhibits, the absolute variation between the lowest and the highest observation approximate is 1.50 percent. Given this fact, we hold that our results are robust and not biased from the selected inception period.

Table 5.8: **Multi-Asset Robustness Test**

Table 5.8 establishes the robustness for five multi-asset momentum strategies based on *J months* lagged returns and held for subsequently *K months*. Each strategy is lagged on a 1 to 11 months basis to test the alpha robustness of the multi-asset momentum. The lags are shown in the first row and the portfolios are listed in the first column. The sample period is December 1999 to December 2011.

	Portfolio Selection (J,K)				
Number of Lags	**1-1**	**3-3**	**6-6**	**9-9**	**12-12**
	15.90	9.30	9.19	11.23	11.29
1st	16.16	9.52	9.33	10.91	12.23
2nd	16.17	9.58	9.46	10.83	12.08
3rd	16.52	9.87	9.26	10.91	11.68
4th	17.55	9.67	9.85	11.10	11.07
5th	17.26	9.67	9.44	11.29	11.15
6nd	16.91	9.98	9.60	11.02	10.75
7th	17.63	9.94	9.73	10.93	10.91
8th	16.02	9.64	10.17	11.28	11.21
9th	15.62	9.96	10.67	11.26	11.54
10th	16.53	10.02	9.98	11.22	10.21
11th	16.96	9.60	9.11	10.65	9.58
Range	**2.00**	**0.72**	**1.55**	**0.64**	**2.64**

5.7 Summary

Chapter 5 illustrated that investors engaged in multi-asset investing are able to construct momentum models that significantly capture the underlying momentum effect across the included asset classes. By following Jegadeesh and Titman (1993), investors are able to model various formation and holding periods to efficiently exploit the momentum existence. Thus, by shorting the worst performing quartiles to fund long positions in the best performing quartiles, investors are able to invest at a zero cost as well as to capture the long-short alpha produced by the multi-asset momentum model. In this thesis we produced 75 momentum portfolios from a data sample covering 50 asset classes over the sample period December 2009 to December 2011.

We found that investors invested in the benchmark portfolio would earn a significant excess return of 9.19 percent (3.11). The strongest momentum return was observed in the 6-12 portfolio of 18.31 percent (6.80) followed by the frequently applied 12-3 portfolio that earned a significant abnormal return of 10.49 percent (4.39). Only the 3-9 and the 1-3 portfolio proved only to be significant at a 90 percent significant level.

In accordance to previous equity momentum literature, we found that the equity carve out was highly significant in 21 of the 25 equity momentum portfolios. The same conclusion could be drawn form the debt carve that proved to be the best performing asset class in the sample period. Thus, the debt carve out exhibited the strongest significance of all the broad asset classes. However, this finding does not support Gebhardt et al. (2005), but does support Jostova et al. (2010). Commodities proved to be highly significant in 20 of the 25 portfolios, as we would have expected. The only asset not exhibiting strong momentum persistence was the currency momentum. The momentum findings of the exchange rates proved to be extremely varicoloured, thus we postulate that such asset class could be the most efficient asset class of the four broad asset classes.

Moreover, we found a tendency to that multi-asset momentum was driven by the worst performing deciles. Within five subset portfolios, four portfolios indicated to be driven by the volatile worst performing deciles. We furthermore proved that the multi-asset momentum was not driven by high tracking error and investors engaged in multi-asset momentum investing should expect a moderate information ratio. Moreover, the information ratio proved to attain the highest level at the 1-1 portfolio and the lowest in the 12-12 portfolio, indicating that multi-asset momentum predominantly is profitable in the short run.

Furthermore, we proved that especially commodities and emerging equities were most frequently present in the worst and the best performing deciles, respectively. Thus, we postulate that multi-asset momentum could be driven by such asset classes.

Additionally, we illustrated that the global equity factor, MSCI World, along with the aggregated commodity factor, DJ-UBS, proved to significantly affect the multi-asset momentum as stated above. We noticed that the global bond factor, Barclays Global Aggregate, did not significantly affect the multi-asset momentum, hence we postulate that the bond factor is not the primary driver of the multi-asset momentum. The same was evident for the size-, style- and momentum factor. Given the relatively moderate R^2, we swap the four insignificant factors with four macro factors. This way, we proved that a *low* VIX significantly affected the multi-asset momentum in combination with the equity market factor and the commodity factor. Neither the CTA, CPI nor the TED-spread proved to be significant. These finding lead us to postulate that multi-asset momentum is significantly generated by a positive market movement in equities and commodities accelerated by with a low VIX.

Finally, the out of sample evidence proved that multi-asset momentum would be affected by the sample period and especially positive markets tend to drive the momentum. In the data sample, all rebound markets proved to be profitable to multi-asset momentum investors as opposed to the crash periods. We found that multi-asset momentum proved to be most profitable in the cycle from December 1999 to December 2007. However, the fact that the multi-asset momentum can be affected by the applied sample period does not mean that investors would achieve the same results by altering the inception date. We found that the results was strongly robust as we lagged the inception date by up to 11 months.

We can deduce from chapter 5 that multi-asset momentum is highly significant utilizing the applied data sample and sample period. We can furthermore deduce that the multi-asset momentum was primarily driven by positive equity and commodity markets, which was supported by the factor analysis. We are additionally able to deduce from the factor analysis that a low VIX significantly proved to affect the multi-asset momentum. Finally, we can deduce that the profitability of multi-asset momentum is dependent on the selected time frame, as especially bear markets in equity and commodity markets (accelerated by the implied high VIX) would erode the multi-asset significance.

Chapter 6

Conclusion

In this final chapter, we will recapitulate on the finding from section 3.5, section 4.3 and section 5.7 to clarify the thesis statement of *how investors compose investable multi-asset portfolios that significantly exploit the underlying momentum dynamics of four broad asset classes?.*

We have in chapter 3 illustrated that momentum in US equities was highly significant. The evidence was initiated by Jegadeesh and Titman (1993) who illustrated how investors could compose investable equity momentum portfolios that significantly exploited the underlying momentum dynamics. By dividing the individual equities into deciles, based on their past relative strength performance, investors were able to short the worst performing deciles to fund long positions in the best performing deciles. Following a strategy that looked at the past one year performance and subsequently held the equities for three months, proved to be highly significant to investors as they would annually earn a profit of 12 percent (4.28) on their long-short positions. The evidence was supported during the following decade and was in 1998 initiated in the European equity market. Rouwenhorst (1998) illustrated how the Jegadeesh and Titman (1993) could be applied in the European equity market to significantly earn a profit of 13.9 per cent (4.02). He furthermore proposed that a common factor could be the catalyst of equity momentum due to high correlation structure between US and European Momentum. In addition, chapter 3 illustrated that the momentum evidence in bonds, commodities and currency was indefinite based on the short publication body. Despite this fact, both Serban (2010) and Menkhoff et al. (2012) found the currency momentum strategy significant and profitable. Jovesta et al. (2010) found the corporate high yield momentum to be significant and profitable, but the overall corporate momentum was refused by Gebhardt et al. (2005). Miffre and Rallis (2007) and Shen et al. (2007) supported the former momentum evidence in currency and found the momentum strategy significant and profitable using the Jegadeesh and Titman (1993) methodology.

We applied this knowledge in chapter 5 and extended the data sample to consist of 50 asset classes sampled in four broad asset classes in the sample period December 2009 to December 2011. We applied the Jegadeesh and Titman (1993) methodology and found that investors invested in the benchmark portfolio would earn a significant excess return of 9.19 percent (3.11). The strongest momentum return was observed in the 6-12 portfolio of 18.31 percent (6.80). Only the 3-9 and the 1-3 portfolio proved to be significant at a 90 percent significant level. The strong equity momentum was furthermore supported as 21 of the 25 equity momentum portfolios proved to be significant and profitable. This was moreover proven for the debt asset class as well as the commodity asset class. However, the currency asset class proved to be the most efficient market of the four as the momentum evidence was inconclusive and varicoloured. We furthermore found a tendency that multi-asset momentum was driven by the worst performing quartiles in which especially commodities and emerging equities were present. Using the arbitrage pricing theory we illustrated that positive movements in a global equity factor and a aggregated commodity factor significantly affected the multi-asset momentum, which was accelerated by a low VIX. The global bond factor did not prove to be significant and neither did the size, style, momentum, CTA, CPI nor TED-spread. Chapter 5 additionally illustrated how sample periods affected the profitability of the multi-asset momentum as especially bear markets eroded the multi-asset significance.

Given the outlined above findings, we are able to conclude that investors are able to compose investable multi-asset portfolios, which significantly exploit the underlying momentum dynamics of four broad asset classes by following the methodology of Jegadeesh and Titman (1993). Following such strategy, investors should expect to earn a significant profit on a 12 months basis from especially their short positions. Additionally investors ought to have high allocations towards the emerging equity and commodity markets as such asset classes proved to be the strongest underlying drivers of the multi-asset momentum, including the VIX. Finally, investors should be careful applying the multi-asset momentum strategy as especially bear markets could erode the profit potential. Investors should ultimately deduce that capital markets are not, ceteris paribus, as efficient as modern finance prescribes and momentum should no longer be perceived as a random market anomaly, but rather a ruling market factor.

So whereas prediction may indeed be difficult, by following a clearly defined methodology, investors are able to utilise a zero-cost long-short trading strategy as a mean of capturing a predicted - and most importantly profitable - future momentum.

Notes

[1]Figure 2.1 was produced by the author of the thesis

[2]Figure 2.2 was produced by the author of the thesis

[3]Figure 2.3 was produced by the author of the thesis

[4]Random Walk notations relate to the Global Stock Markets class taught by Professor Ole Risager

[5]Figure 2.4 was produced by the author of the thesis

[6]Figure 2.5 was produced by the author of the thesis

[7]t-statistics are henceforth reported in brackets

[8]JeTi1993 is an acronym for Jegadeesh and Titman, 1993

[9]CoKa1998 is an acronym for Conrad and Kaul, 1998

[10]JeTi2001 is an acronym for Jegadeesh and Titman, 2001

[11]Figure 5.1 was produced by the author of the thesis

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Chapter 7

Appendix

Calculations and Econometric Measures

Geometric Mean

$$r_t = ((1 + r_t)(1 + r_{t+1})...(1 + r_{t+n}))^{1/n} - 1 \tag{7.1}$$

Arithmetic Mean

$$r_t = \frac{1}{\sum_{t=1}^{n} w_i} \tag{7.2}$$

Welch Test Statistics

$$t - test = \frac{\overline{r_{MOM}} - \overline{r_{POP}}}{\sqrt{\frac{\sigma^2_{MOM}}{n_{mom}} + \frac{\sigma^2_{POP}}{n_{POP}}}} \tag{7.3}$$

χ^2 Test Statistics

$$\chi^2_{LB} = n(n+2) \sum_{i=1}^{n} \frac{p(j)^2}{n-j} \tag{7.4}$$

Z-score

$$z - score = \frac{x - \bar{x}}{\sigma} \tag{7.5}$$

Variance Inflation Factor (Multicollinearity)

$$VIF_i = \frac{1}{1 - R_i^2} \tag{7.6}$$

Value Inclusion Factor (Fundamental Indexing)

$$\begin{aligned} z - score(value) = [zscore(\tfrac{B}{P}) &+ zscore(\tfrac{EPS}{P}) + zscore(\tfrac{E}{TD}) \\ &+ zscore(\tfrac{DPS}{P}) + zscore(\tfrac{CA}{CL})] \cdot \tfrac{1}{4} \end{aligned} \tag{7.7}$$

$$\begin{aligned} z - score(growth) = [zscore(\tfrac{P}{B}) &+ zscore(\tfrac{P}{EPS}) + zscore(\tfrac{TD}{E}) \\ &+ zscore(\tfrac{P}{DPS}) + zscore(\tfrac{CL}{CA})] \cdot \tfrac{1}{4} \end{aligned} \tag{7.8}$$

We only use the company as value contributor if

$$valuez - score > 0 \mid growthz - score < 0$$

and

we only use the company as growth contributor if

$$valuez - score < 0 \mid growthz - score > 0$$

Figure 7.1: **Equity and Debt Performance**

Figure 7.1[12] illustrates the performance of the included debt and equity indices in the sample period from December 1999 to December 2012.

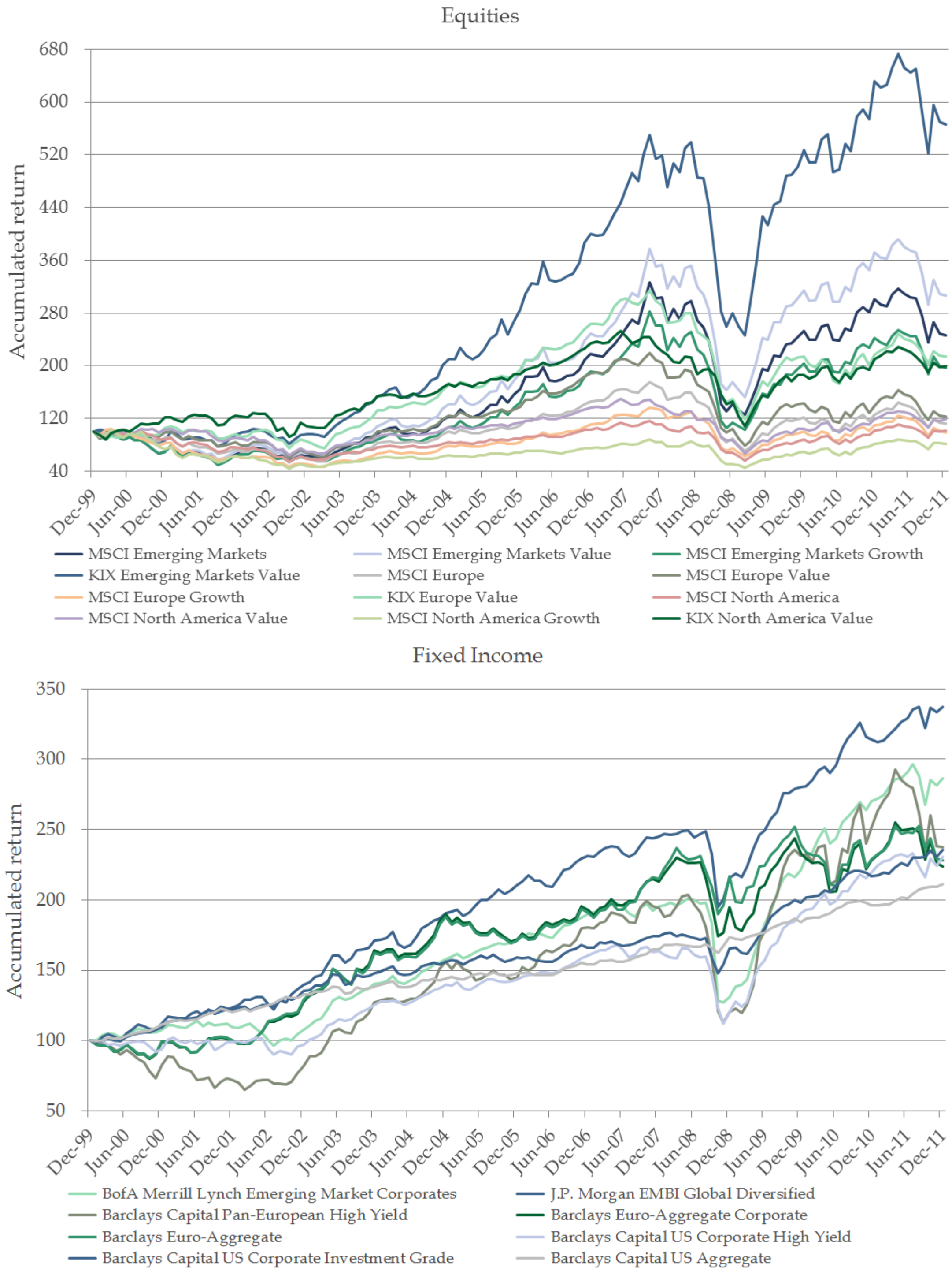


Figure 7.2: **Commodity and Currency Performance**

Figure 7.2[13] illustrates the performance of the included commodity indices and currencies in the sample period from December 1999 to December 2012.

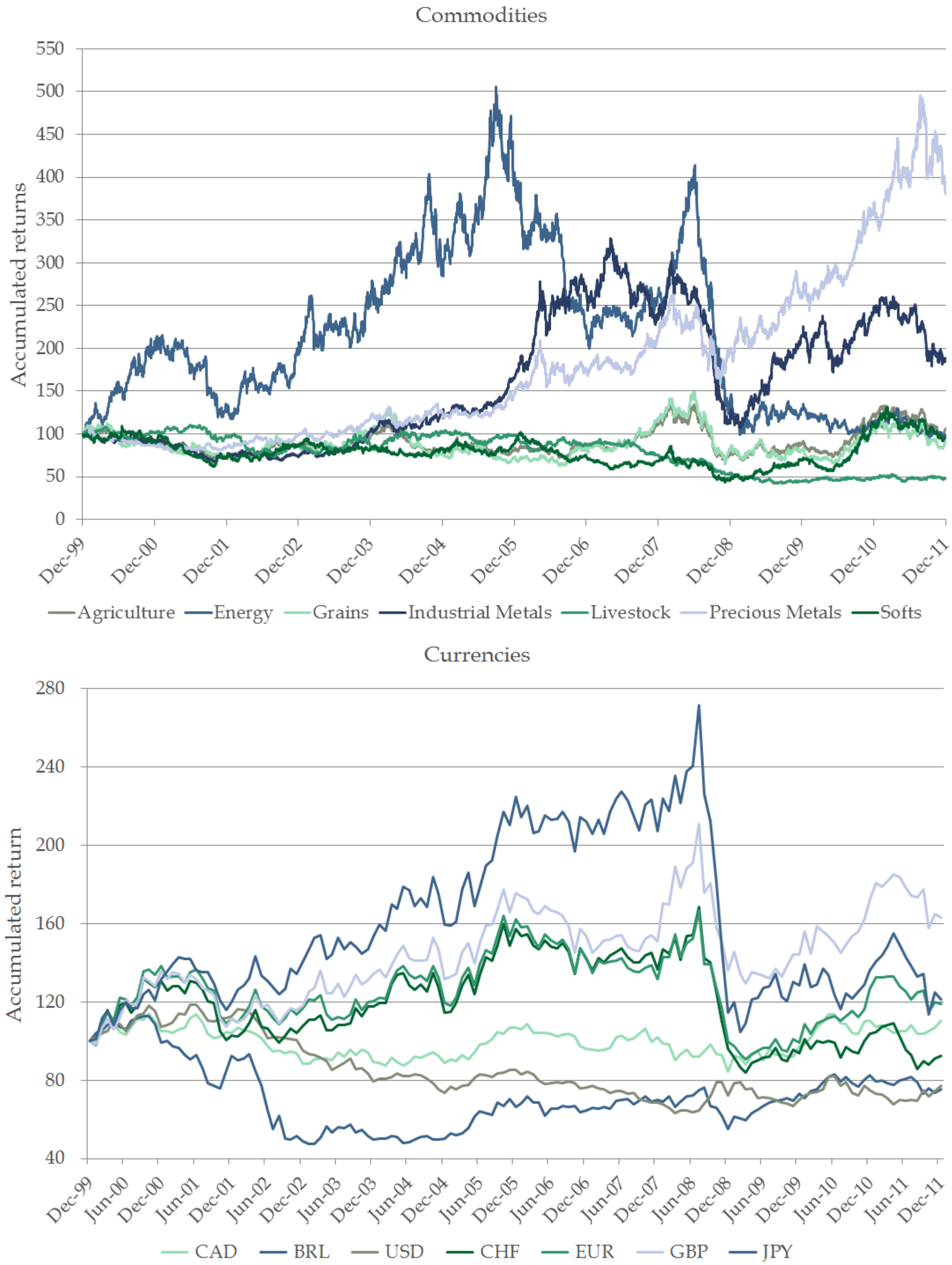


Figure 7.3: **Distribution and Asset Class Ranking**

Figure 7.3[14] (A) illustrates the distribution of Q1, Q2, Q3, and Q4 in the sample portfolios. (B) illustrates the ranking of Q1 and Q4.The sample period is Demcember 1999 to December 2012.

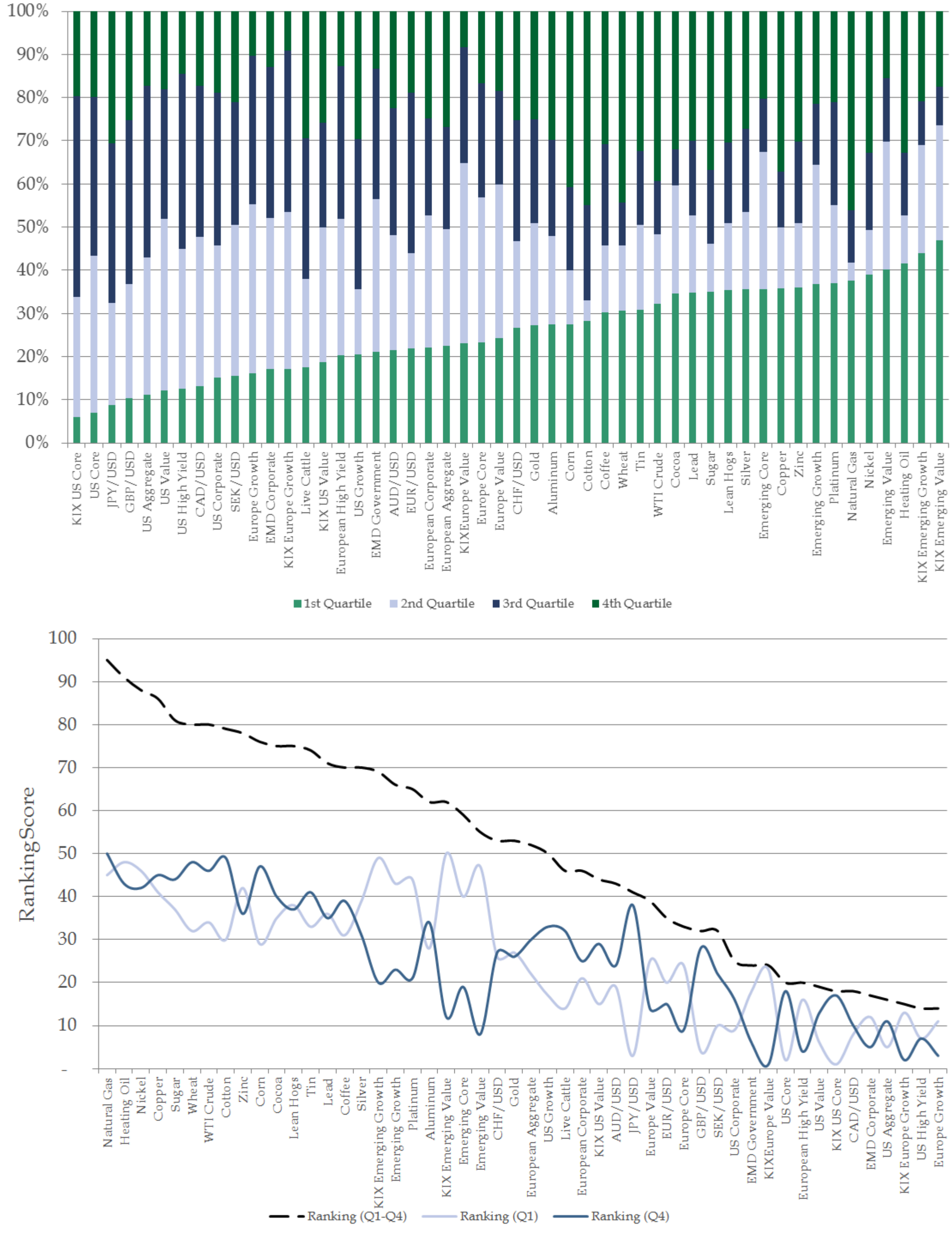
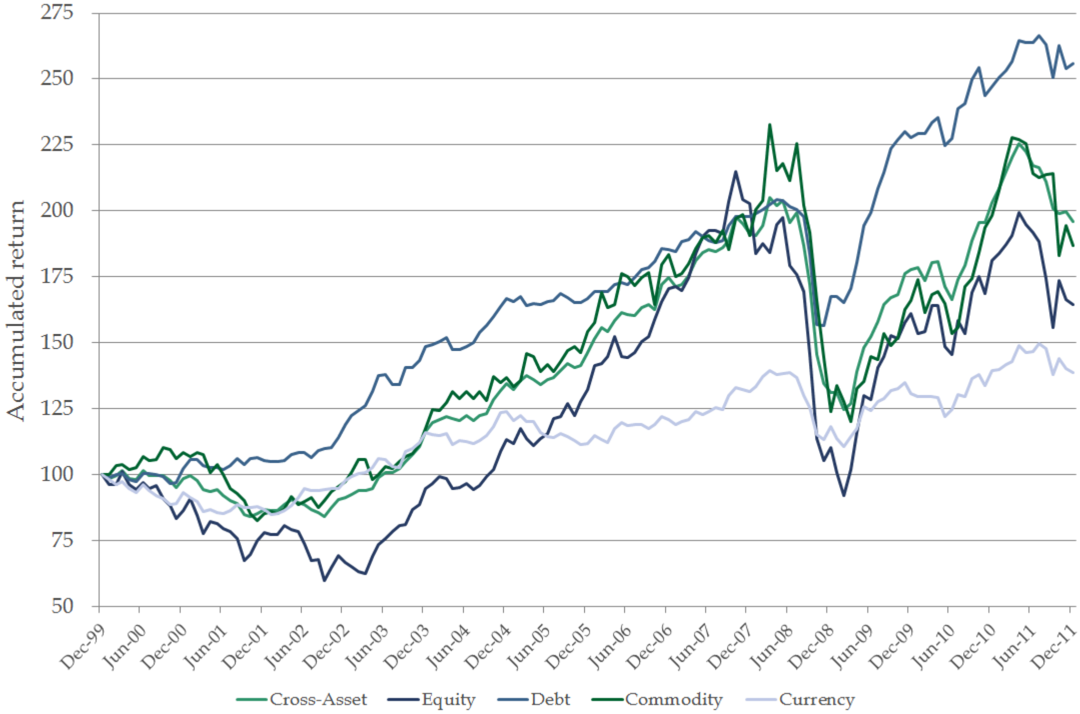


Figure 7.4: **Performance of Asset Classes**

Figure 7.4[15] illustrates the accumulated return of the individual asset classes ass well as the multi-asset momnetum.



Visual Basic Programming

VBA for Portfolio Generation

```
Sub Return Generation()
Dim F As Long
Dim H As Long
Dim i As Long
Dim j As Long
Dim A As Long
Dim B As Long

Sheets("Compilation").Activate
'Formation Period
F = ActiveSheet.Range("D4").Value
'Holding Period
H = ActiveSheet.Range("E4").Value
'Portfolio selection
A = ActiveSheet.Range("C4").Value
'Lags
B = ActiveSheet.Range("B4").Value

Worksheets("Holding MOM").Range("M5:BJ149").ClearContents

For j = 0 To 49 Step 1
For i = 0 To 149 Step 1

Sheets("Formation MOM").Activate
If ActiveSheet.Range("BR8").Offset(i + B, j).Value = A Then

Sheets("Holding MOM").Activate
ActiveSheet.Range("M" 5 + i + B ":M" 4 + F + i + B).Offset(0, j).Value = 0
ActiveSheet.Range("M" 5 + F + i + B ":M" 4 + F + H + i + B).Offset(0, j).Value = 1
i = i + H + F
Else
End If
Next i
Next j
End Sub
```

VBA for lagged Winners

```
Option Explicit
Sub LagMomentum()

Sheets("Compilation").Activate
'Portfolio selection
ActiveSheet.Range("C4").Value = 1

'Formation Period
ActiveSheet.Range("D4").Value = 12
'Holding Period
ActiveSheet.Range("E4").Value = 12
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("c8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 9
'Holding Period
ActiveSheet.Range("E4").Value = 9
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("u8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 6
'Holding Period
ActiveSheet.Range("E4").Value = 6
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("am8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 3
'Holding Period
ActiveSheet.Range("E4").Value = 3
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("be8").PasteSpecial Paste:=xlPasteValues
```

```
'Formation Period
ActiveSheet.Range("D4").Value = 1
'Holding Period
ActiveSheet.Range("E4").Value = 1
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("bw8").PasteSpecial Paste:=xlPasteValues

End Sub
```

VBA for lagged Losers

```
Option Explicit
Sub LagMomentum()

Sheets("Compilation").Activate
'Portfolio selection
ActiveSheet.Range("C4").Value = 4

'Formation Period
ActiveSheet.Range("D4").Value = 12
'Holding Period
ActiveSheet.Range("E4").Value = 12
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("c8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 9
'Holding Period
ActiveSheet.Range("E4").Value = 9
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("u8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 6
'Holding Period
ActiveSheet.Range("E4").Value = 6
Call Return Generation
Sheets("Compilation").Activate
```

```
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("am8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 3
'Holding Period
ActiveSheet.Range("E4").Value = 3
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("be8").PasteSpecial Paste:=xlPasteValues

'Formation Period
ActiveSheet.Range("D4").Value = 1
'Holding Period
ActiveSheet.Range("E4").Value = 1
Call Return Generation
Sheets("Compilation").Activate
ActiveSheet.Range("B8:B152").Copy
ActiveSheet.Range("bw8").PasteSpecial Paste:=xlPasteValues

End Sub
```

LaTex Setup

renewcommandbaselinestretch1.5

usepackage[margin=3cm]geometry

documentclass[10pt,oneside]book

usepackage[danish,english]babel

usepackageamsmath,amssymb

usepackage[latin1]inputenc

usepackage[round]natbib

usepackage[all, knot]x y

usepackagesubcaption

usepackage[T1]fontenc

usepackagegraphicx

usepackageapacite

usepackagerotating

usepackagemulticol

usepackagecaption

usepackagelscape

usepackagefloat

xyoptionarc

Figure 7.5: **SAS-output: Anderson-Darling Normality Test**

Distribution analysis of: 6-6
The UNIVARIATE Procedure

Variable: 6-6

Moments

N	144	Sum Weights	144
Mean	0.0095	Sum Observations	1.36615169
Std Deviation	0.0738	Variance	0.00544259
Skewness	-0.8617	Kurtosis	3.03541863
Uncorrected SS	0.7913	Corrected SS	0.77829075
Coeff Variation	777.62	Std Error Mean	0.00614783

Basic Statistical Measures

Location		Variability	
Mean	0.0095	Std Deviation	0.07377
Median	0.0185	Variance	0.00544
Mode	.	Range	0.5563
		Interquartile Range	0.08966

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.951819	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.068199	Pr > D	0.0977
Cramer-von Mises	W-Sq	0.177705	Pr > W-Sq	0.0099
Anderson-Darling	A-Sq	1.276514	Pr > A-Sq	<0.0050

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Figure 7.6: **SAS-output: Durbin-Watson Autocorrelation Test**

Regression Analysis with Autoregressive Errors
The AUTOREG Procedure

Dependent Variable: 6-6

Ordinary Least Squares Estimates

SSE	0.13602927	DFE	137
MSE	0.0009929	Root MSE	0.03151
SBC	-559.47359	AIC	-580.26229
MAE	0.02389964	AICC	-579.43876
MAPE	632.656466	HQC	-571.81494
Durbin-Watson	1.9887	Regress R-Square	0.8114
		Total R-Square	0.8114

Miscellaneous Statistics

Statistic	Value	Prob	Label
Durbin's t	0.047	0.4813	Pr > t
Normal Test	3.0503	0.2176	Pr > ChiSq

Durbin-Watson Statistics

Order	DW
1	1.9887

Parameter Estimates

	DF	Estimate	SSE	t Value	Pr > |t|
Intercept	1	-0.001017	0.002821	-0.36	0.7191
Mkt-RF	1	0.6412	0.0574	11.16	<.0001
SMB	1	0.0795	0.0785	1.01	0.3128
HML	1	0.1068	0.0792	1.35	0.18
UMD	1	-0.2209	0.333	-0.66	0.5082
BOND	1	0.5392	0.153	3.52	0.0006
DJUBS	1	0.9702	0.0502	19.31	<.0001

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Figure 7.7: **SAS-output: White's Homoscedasticity Test**

Linear Regression Results
The REG Procedure

Model: Linear_Regression_Model

Dependent Variable: 6-6

Number of Observations Read	144
Number of Observations Used	144

Analysis of Variance

Source	DF	SSE	MSE	F Value	Pr > F
Model	6	0.58528	0.09755	98.24	<.0001
Error	137	0.13603	0.0009929		
Corrected Total	143	0.72131			

Root MSE	0.03151	R-Square	0.8114
Dependent Mean	0.00772	Adj R-Sq	0.8032
Coeff Var	408.23884		

Parameter Estimates

Variable	DF	Parameter	S.E.	t Value	Pr > |t|
Intercept	1	-0.00102	0.00282	-0.36	0.7182
Mkt_RF	1	0.64118	0.05744	11.16	<.0001
HML	1	0.10687	0.07924	2.35	0.0017
SMB	1	0.07968	0.07845	5.02	0.0061
UMD	1	-0.22093	0.33302	-4.66	0.0508
BOND	1	0.53961	0.15303	3.53	0.0006
DJUBS	1	0.97029	0.05024	19.31	<.0001

Generated by the SAS System ('Local', W32_VSPRO) on 12. oktober 2012 at 3:49:06 PM

Figure 7.8: **SAS-output: VIF-score for Multicollinearity Test**

Linear Regression Results
The REG Procedure

Model: Linear_Regression_Model

Dependent Variable: 6-6

Number of Observations Read	144
Number of Observations Used	144

Analysis of Variance

Source	DF	SSE	MSE	F Value	Pr > F
Model	6	0.58528	0.09755	98.24	<.0001
Error	137	0.13603	0.0009929		
Corrected Total	143	0.72131			

Root MSE	0.03151	R-Square	0.8114
Dependent Mean	0.00772	Adj R-Sq	0.8032
Coeff Var	408.23884		

Parameter Estimates

Variable	DF	Parameter	S.E.	t Value	Pr > |t|	VIF
Intercept	1	-0.00102	0.00282	-0.36	0.7191	0
Mkt-RF	1	0.64124	0.05744	11.16	<.0001	1.17934
SMB	1	0.07948	0.07845	1.01	0.3128	1.27604
HML	1	0.10678	0.07924	1.35	0.18	1.18943
UMD	1	-0.22091	0.33304	-0.66	0.5082	1.05227
BOND	1	0.53917	0.15303	3.52	0.0006	1.05759
DJUBS	1	0.97025	0.05023	19.31	<.0001	1.0259

Generated by the SAS System ('Local', W32_VSPRO) on 12. oktober 2012 at 3:49:06 PM

Table 7.1: **Excel-output: Ljung-Box χ^2 test-statistics**

Lag	**Q-stat1**	**Q-stat2**	**Q-stat3**	**Q-stat4**	**Q-stat5**
1	8.513	38.96	0.016	55.26	45.56
2	8.822	51.36	0.956	108.9	60.28
3	13.71	53.70	1.444	136.5	67.03
4	22.33	53.77	2.712	149.9	69.46
5	24.54	57.07	3.616	158.3	72.60
6	27.96	59.26	4.384	161.0	81.59
7	31.99	60.12	4.816	161.9	89.04
8	32.05	60.14	4.818	162.2	96.80
9	32.05	61.13	4.854	162.4	97.33
10	32.07	61.26	5.182	162.7	97.35
11	32.19	61.27	6.872	164.3	97.39
12	32.75	61.34	8.947	165.0	98.26
13	32.98	63.86	9.004	168.9	101.4
14	34.51	69.19	10.30	171.2	104.0
15	34.66	73.90	12.51	175.5	109.1
16	34.71	76.64	12.70	178.1	120.2
17	35.91	76.65	12.85	181.3	126.7
18	35.95	78.37	13.28	182.7	132.6
19	36.39	82.78	13.28	185.4	140.3
20	36.62	91.62	13.47	186.6	145.2
21	36.82	118.4	13.47	189.4	148.9
22	38.04	125.3	13.53	189.9	152.1
23	39.71	130.2	14.90	190.5	156.0
24	40.50	132.0	15.49	192.6	164.9
25	40.62	132.4	15.49	194.6	170.9
26	40.97	132.4	15.50	198.9	172.9
27	41.24	132.9	15.50	200.7	173.5
28	41.33	133.1	15.95	203.2	176.1
29	41.82	133.3	15.95	205.4	178.6
30	42.48	134.8	16.23	206.7	181.8
31	44.13	135.3	16.97	207.9	185.2
32	44.56	135.3	17.23	208.3	186.7
33	47.50	135.5	17.74	208.9	189.2
34	47.56	138.5	17.77	208.9	190.3
35	47.56	143.8	20.58	209.0	190.4
36	47.61	148.2	20.76	209.2	191.2