An Empirical Test of German Stock Market Efficiency

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Declaration of Authorship

I hereby confirm that I have authored this master thesis independently and without use of other than the indicated resources. All passages, which are literally or in general matter taken out of publications or other resources, are marked as such.

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Notation

Symbol / Abbreviation	Description
ι	Column vector of ones
R_m	Return on market portfolio
R_p	Return on asset portfolio
R_i	Return on asset i
r_f	Return on risk-free asset
β_i	Index of systematic risk for asset i
β_p	Index of systematic risk for portfolio
APT	Arbitrage Pricing Theory
BGB	Bankgesellschaft Berlin
BM	Benchmark
CAPM	Capital asset pricing model
CFS	Cash flow per share
EMH	Efficient market hypothesis
EPS	Earnings per share
GLS	General least squares
i.i.d.	Independently and identically distributed
OLS	Ordinary least squares

Chapter I
Introduction

There currently exists a considerable amount of evidence of the correlation of major international equity markets (Rouwenhorst 1998 and Schiereck, De Bondt and Weber 1999) as well as the strikingly common determinants of expected stock returns that these markets share (Haugen and Baker 1996). From these indications, it seems quite reasonable to deduce that successful methods of exploiting market inefficiencies to attain abnormal profits in one market might translate to similar profits in another similarly behaved market. This paper focuses on applying a multifactor stock screening method called CAN SLIM™, which has recorded highly positive abnormal returns in the U.S., to the German market, in an attempt to capitalize on these aforementioned ideas.

CAN SLIM™ was developed by William O'Neil, a well-known American investment analyst, and is an acronym with each letter representing a different criterion for selecting stocks. These seven factors are a combination of "hard", objective and able to be programmed in a computer language, and "soft", of a more subjective nature for which programming is difficult or impossible, characteristics. However, this paper incorporates only the hard factors into the selection approach as it was written in collaboration with the Quantitative Research Department of Bankgesellschaft Berlin (BGB), an endeavor aimed at developing a profitable long/short equity selection methodology to be implemented into BGB's trading system. Since CAN SLIM™ strongly relies on precisely timing the purchase and sale of stocks, executing a CAN SLIM™ screening requires that the entire German CDAX® investment universe be scanned on a daily basis, after which the portfolios must be adjusted accordingly. Considering this volume of data and amount of computation, it is only feasible to implement a programmable approach.

The organization of this paper is broken into two main parts. First, Chapter II presents the underlying theoretical foundations behind the application and evaluation of the CAN SLIM™ method. The chapter begins with an overview of the concept of market efficiency, followed by a description of different methodologies used to test for market efficiency, then explanations of apparent violations of market efficiency and lastly, an outline of two popular models for measuring expected return. Using the principles presented in Chapter II, Chapter III continues with an empirical analysis of CAN SLIM™ in the German market. Before CAN SLIM™ is directly applied to the CDAX® investment universe, an initial screening of the hard factors is performed in order to determine their relevancy. After establishing a relationship between these factors and stock price, a preliminary CAN SLIM™ screening is executed, followed by a full CAN SLIM™ screening which introduces the element of timing purchases and

sales. Finally, Chapter IV concludes the paper with a discussion of the results of the empirical analysis and various issues that may impact the findings.

Chapter II
Theoretical Foundations

1 Market Efficiency

Efficiency, in the context of capital markets, is commonly assumed to refer to the incorporation of the expectations and information of all market participants into the prices of financial assets. If markets are sufficiently competitive, and therefore efficient, then microeconomic theory states that investors cannot earn abnormal profits from their investment strategies. This concept of an efficient capital market has been continuously developed, studied, tested and challenged ever since the French mathematician Bachelier introduced the notion in his Ph.D. thesis in 1900.

In his work, Bachelier recognized that "past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes". He concluded that commodity prices fluctuate randomly, which was empirically supported by Cowles (1933), however largely ignored until Cootner (1964) published Bachelier's contribution in English.

The introduction of electronic computers into time series research in the 1950's enabled economists to analyze the behavior of lengthy economic time series, fueling research on the topic of efficient markets. Samuelson (1965) expanded on Bachelier's theory in his article "Proof that Properly Anticipated Prices Fluctuate Randomly." This work, considered the beginning of modern economic literature, asserts that "if one could be sure that a price would rise, it would have already risen" and explains changes in price with the random walk model.

1.1 Random Walk Model

Although the origins of the random walk model began with Bachelier, Pearson (1905) explained a random walk with an analogy to a drunk who staggers in an unpredictable and random fashion. The drunk is just as likely to end up where he began his stagger than at any other point.

More formally, general random walks are stochastic processes satisfying

(II.1)
$$X_t = X_0 + \sum_{k=1}^{t} Z_k, \quad \text{where } t = 1, 2, \ldots$$

with independent, identically distributed (i.i.d.) increments Z_k. This means that at time t, the increment Z_{t+1} is independent of the past values $X_0, \ldots, X_t$ so that the best

prediction for X_{t+1} is simply $X_t + \mathrm{E}[Z_{t+1}]$. With an additional assumption that $E[Z_k] = 0$ for all *k*, Bachelier postulated "the best prediction for the value tomorrow is the value today."

1.2 Efficient Market Hypothesis

Widely acknowledged today, the *Efficient Market Hypothesis* (EMH) is a historical compilation of work, which begins with Bachelier's foundations. The EMH has historically been subdivided into three categories based on Roberts' (1967) classical taxonomy of information sets:

Weak form efficiency: Prices fully reflect historical information of past prices and returns.

Semi-strong form efficiency: Prices fully reflect all information known to all market participants (public information).

Strong form efficiency: Prices fully reflect all information known to any market participant (public and private information).

From this idea of information sets, Fama (1970) assembled a comprehensive review of theoretical and empirical evidence of market efficiency in which he deems an efficient market as "a market in which prices always 'fully reflect' available information." In an efficient market, trading on available information fails to provide an *abnormal return*. In order to prove or disprove the EMH, a model of "normal" returns must be specified against which the actual returns can be compared. Abnormal returns, the difference between the return on a security and its expected return, are forecasted using the chosen information set. If abnormal returns are found to be unforecastable or "random", the EMH is not rejected. To clarify, abnormal returns should not be confused with excess returns, which are defined as the difference between the actual return and the risk-free rate.

Implicit to the EMH is the precondition that the cost of information acquisition and trading are equal to zero. However, these costs are clearly positive, driving Fama (1991) to revise his definition of the EMH to a weaker and economically more sensible version stating "prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed marginal costs." Most recently, Fama (1998) modified his definition once again, an adjustment which spawned from the growing body of empirical research of all three forms of the EMH. This definition states that in an efficient market "the expected value of abnormal returns is zero, but chance generates deviations from zero (anomalies) in both directions."

Although the EMH has been the central proposition in finance for nearly thirty years, the subject of literally thousands of journal articles, there is amazingly still no consensus among financial economists whether or not markets are efficient. While Fama's definitions are arguably the most well known, the EMH can be expressed in a number of alternative ways, not all of which are equivalent, with differences that can be subtle, technical and esoteric. Hence, the definition of the EMH is a "moving goalpost" of sorts, as being tested and challenged. The methods and problems of testing the EMH will be discussed in following sections.

1.3 Testing Market Efficiency

Before explaining methods of testing each the three forms of market efficiency, it is necessary to first clarify the concept by stating that market efficiency is consistent with the *fair game* process of determining prices. The fair game model simply states that there is no way to use information available at time *t* to earn a return greater than that which is consistent with risk inherent in the security.

The information referred to by the fair game model varies with the type of market efficiency being tested. For weak form tests, information can include past history of stock prices, company characteristics, market characteristics and the time of year. Tests for weak form market efficiency are, more generally, referred to as *tests of return predictability*. For semi-strong form tests, information is defined as the announcement of information. These studies of such announcements are termed *event studies*. For strong form tests, information refers to all information, both public private, that is available to any investor. Strong form tests aim to reveal whether or not investors exist who have superior abilities that allow them to make abnormal profits.

The fair game model is a slightly less restricted version of the random walk model in that the fair game model does not require returns to be independent nor identically distributed over time. For an example that holds for the fair game model but not the random walk model due to this extra i.i.d. assumption, consider a firm that increases its debt and risk over successive periods, resulting in increased expected and actual returns. In this case, an obvious correlation will result in the sequence of past returns that can be used to predict future returns. However, since the expected return increases due to increasing risk, this information cannot be used to earn an abnormal return.

Although the EMH is consistent with all three forms of the fair game model (and vice versa), the EMH does not share the same relationship with the random walk model. While the EMH holds whenever the random walk hypothesis holds, the same is not true for the reverse case. The random walk process produces i.i.d. returns from an information set of past returns, addressing weak form efficiency only. Therefore, the EMH does not necessarily support the random walk hypothesis as the EMH is a more general idea, which encompasses all three forms of efficiency.

At this point, it is important to clarify the following point that is often a source of confusion; if the EMH holds, there is not any implication that the expected return of any security is zero. In fact, one would expect that the return would be positive and related to the amount of risk, with the riskier securities offering higher returns. The correct implication is that past information does not reveal anything about the magnitude of the deviation of today's return from the expected return.

1.3.1 Tests of Return Predictability

As previously mentioned, tests of return predictability test the weak form of the EMH, and use historical information to look for patterns in returns that can be taken advantage of to generate profits. A number of studies have been performed in this area, all which search for different types of market inefficiencies. The majority of literature on this topic focuses on studies performed on American markets, including the papers from which the information in this subsection was obtained. To mention each study and result is beyond the scope of this paper, however in the remainder of this subsection, an overview of the most important findings from various tests of return predictability will be discussed.

1.3.1.1 Time Patterns

Time patterns in returns have been extensively researched, resulting in discoveries that returns are systematically higher depending on the time of the day, the day of the week or the month of the year. The *weekend effect* refers to the well-documented phenomena that the average returns are reliably negative over weekends (from Friday's market close to Monday's open)[1]. Harris (1986) also found that the decline continued through the first forty-five minutes of trading on Monday, after which returns resembled those of any other day. However, since the weekend effect was first documented, it seems to have disappeared of at lest substantially attenuated. Furthermore, there has been no profitable trading strategy based on the weekend effect to date.

The *turn-of-the-year* effect describes the pattern that returns in January are substantially higher than returns in other months, especially for small-capitalization stocks[2]. This effect is also referred to as the *January effect.* Gultekin (1983) studied this effect in seventeen countries including the United States. He found turn-of-the-year effects in all seventeen markets, with the most significant effects occurring in non-U.S. markets. Unlike the weekend effect, the turn-of-the-year effect has not completely disappeared since it was originally documented which is hard to reconcile with the EMH.

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[1] See Gibbons and Hess (1981) and French (1980).
[2] See Fama (1991), Keim (1983) and Reinganum (1983).

Drawing conclusions from the multitude of tests that have discovered time patterns in returns is difficult. However, a few plausible explanations exist. First, it is possible that these patterns are simply random and are bound to be discovered with hundreds of researchers examining the same data set. This phenomenon is called *data-snooping*; it occurs when identical, or at least positively correlated, data is used over and over to refine or reiterate results of studies. Second, it is possible that these patterns are induced by market structure and order flow. Last, perhaps markets are inefficient since in an efficient market, these patterns would disappear as soon as investors exploited them. Whatever the reason for these time patterns, in most cases no profitable trading strategies exist since the size of the abnormal returns is not large enough to outweigh the transaction costs.

1.3.1.2 *Predicting Returns From Past Returns*

Tests of return predictability also include tests that check to see if returns can be predicted from past returns over short-term horizons. Such tests include *correlation tests* in which correlation coefficients for today's return and past returns are examined for the existence of a linear relationship, *runs tests* which examine the patterns in the sign of price changes and *filter rules* which implement timing strategies of purchasing, selling and short-selling depending on preestablished price barriers. Although there is some evidence from both correlation and runs tests that a small positive relationship between today's and yesterday's returns exists (Fama 1965), due to transaction costs the relationship is too small to be used to generate any profits.

1.3.1.3 *Anomalies*

Market anomalies are empirical results that describe the relationship between firm characteristics and abnormal returns. The existence of anomalies is difficult to reconcile with the EMH and could indicate that inefficiencies exist since in an efficient market it should not be possible to earn abnormal profits based on observable firm characteristics.

While several anomalies have been documented in various publications, three of the most frequently discussed include the *value effect*, the *momentum effect* and the *size effect*. The value effect refers to the observation that stocks with high book-to-market values seem to realize positive abnormal returns (Fama and French 1992) while the momentum effect describes the phenomenon that recent past winners outperform recent past losers (Jegadeesh and Titman 1993). The size effect anolmaly has attracted an especially large amount of attention. Banz (1981) first documented the size effect when he discovered that from 1931-75, the monthly returns of the fifty smallest stocks listed on the New York Stock Exchange outperformed the fifty largest by an average of one percentage point on a risk-adjusted basis, using the *capital as-*

set pricing model (CAPM) to estimate expected returns. Like the weekend effect, the size effect has disappeared or at least been dramatically reduced since the initial publication of papers that revealed it (Schwert 2003).

In an attempt to explain the size effect, it is argued that the risk parameter β in the CAPM model might be underestimated for small firms. This could be due to the fact that small firms are subjected to nonsynchronous trading since they trade less often than large firms, thus leading to an underestimation of β (Roll 1981 and Reinganum 1981). It could also be that firms that have become small have changed their economic characteristics, growing riskier over time since smaller firms have a lower survival probability. Since β is measured using historical returns, perhaps it does not capture the current economic risks (Christie and Hertzel 1981).

Another explanation for the size effect and other anomalies is that the model chosen to measure expected returns is inadequate. Under this reasoning, it follows that anomalies may seem to exist when firm characteristics contribute to a risk variable that is unrepresented in the model. Using the size effect anomaly as an example, if the β's in the CAPM model are systematically underestimated for small firms, then the expected returns for small firms calculated from the model would be too low, and thus there would seem to be a positive abnormal return when in reality, none exists. Once the previously unaccounted for risk variable is taken into account, the relationship between firm characteristics and abnormal returns disappears. If a model is misestimated in such a way, it can account for the presence of anomalies. This discussion of choosing a proper model to estimate expected returns continues in Section 1.5.

Additionally, there are many alternative explanations for the existence of anomalies, the first being that such relationships between firm characteristics and abnormal returns are not real and can be explained by the data-snooping phenomenon that was previously described. This idea is supported by the fact that many of the well-known anomalies including the size effect and value effect do not hold up in different sample periods. Many seem to disappear, reverse or attenuate after they are documented and analyzed in academic literature (Schwert 2003). Alternatively, the existence of trading costs, which eliminate the profitability of exploiting strategies that take advantage of anomalies, can explain the continuing existence (but not the origination) of anomalies. Finally, it is possible that markets are just inefficient.

1.3.1.4 *Predicting Long-term Returns from Firm and Market Characteristics*

While trading spreads, commissions and other transaction costs shadow significant doubt on whether short-term mispricing, as discussed in Section 1.3.1.2, can be used to generate abnormal returns, long-term mispricing poses a greater challenge to the EMH. Many papers have documented a small-degree of predictability in the long-run returns on stocks and bonds based on variables of past information relating to stock

market levels and the term and risk structure of interest rates. Examples of such variables for which a positive relationship with returns has been found include short-term interest rates (Fama and Schwert 1977), interest rate term premium (Campbell 1987), earnings and price of the S&P 500 index (Campbell and Shiller 1988) and dividends and price of the S&P 500 index (Fama and French 1998).

The existence of such relationships can be interpreted as market inefficiency. On the other hand, it can also be argued that the expected return changes over time due to changing business conditions and that these changes can be predicted. The latter explanation using time-varying expected returns could explain such patterns, replacing the assumption of abnormal returns, in order to remain consistent with the EMH.

1.3.2 Event Studies

As previously explained, event studies examine the effect of an announcement on share price as a test of the semi-strong form of the EMH. The initial focus of event studies was on the speed of incorporation of information into the share price and trying to determine how long this process takes. However, it is has since been confirmed empirically that prices react quickly to announcements and now commonly assumed that, given market rationality, the effect of an event will be reflected immediately into share prices. Therefore, the aim of event studies has shifted to measuring the effects of an economic event on a firm, normally by looking at changes in the price of common equity although the prices of other securities can also be examined.

Since event studies are widely applicable to events including mergers and acquisitions, earnings announcements, issues of new debt or equity and announcements of macroeconomic variables such as trade deficit, there has been a great amount of research devoted to event studies in finance. The following econometric methodology consisting of seven steps is commonly used when performing an event study with common stock applications[3].

1. *Event definition.* This initial step consists of defining the event of interest and the *event window*, the period over which the security prices will be examined. In practice, the event window usually consists of two days, the day of and day after the announcement, in order to capture price effects which occur after the markets close on announcement day.

2. *Selection criteria.* In order to determine which firms to study, selection criteria must be defined. This criteria may contain but is not limited to being listed on certain exchanges, being a member of a certain industry, or having a certain

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[3] Methodology based on outline from Campbell, Lo and MacKinlay (1997).

market capitalization. At this point, any potential biases introduced through the sample selection methods should be identified.

3. *Normal and abnormal returns.* In order to determine an event's impact, the abnormal return must be measured. The abnormal return ε_{it} is the actual return of the security R_{it} minus the normal return $\mathrm{E}[R_{it} | X_t]$ while the normal return is defined as the expected return if the event did not occur. Thus, the abnormal returns for each firm *i* in every time period *t* in the event window are represented as*:*

(II.2) $$\varepsilon_{it} = R_{it} - \mathrm{E}[R_{it} | X_t]$$

where X_t is the conditioning information for the chosen normal performance model. To model the normal return, a benchmark model must be chosen. Common choices include the market model, multifactor models, CAPM or just simply the return on a market index.

4. *Estimation procedure.* After the normal performance model is selected, the parameters of the model must be estimated using a subset of data called the *estimation window*. Typically, the estimation window consists of a predefined number of days before but not including the event window.

5. *Testing procedure.* Using the estimated parameters from the previous step, the abnormal returns can now be calculated. A testing framework for the abnormal returns should now be defined, including formulating a null hypothesis and determining techniques for aggregating the abnormal returns of individual firms.

6. *Empirical results.* Results obtained from the defined testing procedure can now be presented and further analyzed using various statistical techniques.

7. *Interpretation and conclusions.* Ideally, the empirical results will lead to insights about how the event affects security prices. Explanations should be developed and discrepancies and ambiguities explained.

1.3.3 Testing for Strong Form Efficiency

Tests for strong form efficiency can focus on two issues: whether insider trading results in abnormal returns or if professional investors, analysts and managers have profitable information. When examining insider trading, one would expect that insiders trading on privileged information would purchase before price increase and sell before price decreases and test for such patterns. Alternatively, event study methodology can be employed to test for the presence of abnormal returns earned by insiders. Unless insiders possess superior analytical abilities, any abnormal returns must be due to illegal exploitation of insider information.

Similarly, examining the abilities of investment professionals can test a hypothesis of strong form efficiency. High correlations between actual and forecasted returns can signal superior abilities. Many studies have been performed in this area, however, beginning with earliest studies by Cowles (1933,1944), it is evident that investment professionals do not beat the market. Jensen (1968) found that on a risk-adjusted basis, any advantage that portfolio managers might have is outweighed by fees and expenses. Fama (1991) summarizes similar subsequent studies that find that while some mutual funds have achieved small abnormal returns before expenses, pension funds have underperformed passive benchmarks on a risk-adjusted basis. Although the EMH does not rule out small returns before fees and expenses, investment managers on average are unable to earn enough to compensate for the fees and expenses they incur.

1.4 Problems in Testing Market Efficiency

In the discussion of anomalies, it was postulated that such observed patterns could signal inadequacies of the benchmark model used in measuring abnormal returns as opposed to market inefficiency. This problem is present not only when examining anomalies, but in testing any form of the EMH in which a model for calculating expected returns is used. Any test of efficiency must assume that the chosen equilibrium model correctly defines normal security returns. Tests in which the EMH is rejected could mean that the incorrect equilibrium model has been assumed just as well as market inefficiency. The implication of this situation, called the *joint hypothesis problem*, is that hypotheses of market efficiency can never be rejected.

Selecting an appropriate model is also important when testing market efficiency, however more so for longer-term studies. In event studies, abnormal returns around announcement days are usually large enough so that any measure of expected return will produce similar results. Thus, event studies are relatively insensitive to the model used. However, for studies of longer-term reaction and anomalies, the results are heavily dependent on the chosen model. It follows that in these types of studies, controversy over the implications often arises.

Biases in tests of efficiency also exist and must be carefully considered when evaluating the results and drawing conclusions. Such biases include *data-snooping*, *selection biases* and *survivorship biases*. Data-snooping, as previously discussed, is a bias that is almost impossible to avoid due to the non-experimental nature of economics. Since it is virtually impossible to escape all data-snooping bias in tests of the EMH, they should at least be considered as potential explanations for deviations from the benchmark model.

A selection bias can occur when data availability results in certain subsets of stocks being excluded from the analysis. For example, in studies of analysts' forecasts, access to a historical set of forecasts is often controlled by the investment or-

ganization for which they work. Also, organizations that supply prior forecasts are likely to be those where the organization knows that their techniques will show superior information. Therefore, even if the analysts had no information, academic studies are likely to find that the analysts had an advantage, when in fact, the organizations supplying the data are the ones whose analysts did well by chance.

Survivorship biases are a type of selection bias that occur when selection of firms to be studied is based on knowledge concerning past forecasting skill. In the context of mutual funds, survivorship biases refer to the tendency for poor performers to drop out while strong performers continue to exist, thus resulting in an overestimation of past returns.

Additionally, when testing for market efficiency, one must remember that perfectly efficient markets are unrealistic benchmarks that are unlikely to be observed practice. The presence of market frictions including costs of gathering and processing information, illiquidity and nonsynchronous trading patterns justifies, to a small extent, the existence of abnormal returns. Thus, perfect market efficiency should be thought of as an idealization against which relative efficiency can be measured.

1.5 Models to Measure Expected Return

Choosing an appropriate model to generate expected returns is essential when attempting to measure abnormal returns. In general, models to measure expected return can be classified into two main categories: statistical and economic. Statistical approaches are based upon statistical assumptions of asset return behavior and do not depend on any economic arguments while economic models incorporate additional assumptions concerning investors' behavior. Economic models are advantageous in the respect that they are able to calculate more precise measures of abnormal returns while imposing economic restrictions. Of the number of different available approaches, this section summarizes some of the most popular including the market model which falls in the statistical category as well as the CAPM and multifactor models which represent economic approaches.

1.5.1 Market Model

Single-index models are statistical approaches that are widely used as benchmarks in efficient market tests. These models assume that co-movement between stocks is due to a single common influence or index. Although single-index models can be defined in terms of any influence (e.g., the rate of return on potatoes), the most common index chosen is the rate of return on a market portfolio. This form of the single-index model is called the *market model* which relates the return of any given security R_i to the return of the market portfolio R_m. The market model for any security *i* in period *t* is represented as

(II.3) $$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

(II.4) $$\mathrm{E}[\varepsilon_{it}] = 0, \quad \mathrm{Var}\,\mathrm{E}[\varepsilon_{it}] = \sigma^2_{\varepsilon_i}$$

where:

ε_{it} is the zero mean disturbance term,

α_i is the component of security *i*'s return that is independent of the market's performance and is a random variable and

β_i is a constant that measures the expected change in R_{it} given R_{mt}.

α_i, β_i and $\sigma^2_{\varepsilon_i}$, the parameters of the model, are often obtained from time series regression analysis. Both R_{mt} and ε_{it} are random variables and the use of regression analysis guarantees that they will be uncorrelated such that $\mathrm{cov}(\varepsilon_{it}, R_{mt}) = 0$. Under general conditions, an ordinary least squares (OLS) regression is a consistent method for estimating the market-model parameters. With the assumptions in (II.4), OLS is also an efficient estimator. Departure from these assumptions is discussed at the end of the section. The following visual representation of the time line (Figure II-1) of an event study as discussed in Section 1.3.2, defines notation that is needed to further explain the estimation procedure of the market model.

Figure II-1: Time Line for an Event Study
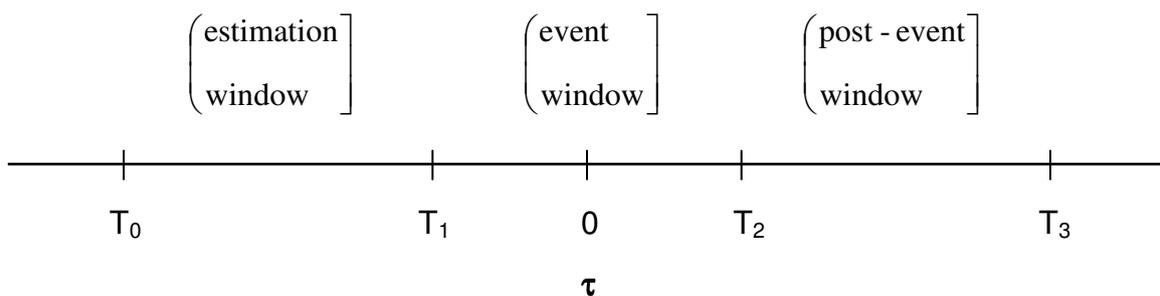
Using this notation, where $\tau = 0$ is the event date, $\tau = T_1 + 1$ to $\tau = T_2$ is the event window and $\tau = T_0 + 1$ to $\tau = T_1$ is the estimation window. The lengths of the estimation and event windows can therefore be represented as $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$, respectively. It follows that the post-event window will be from $\tau = T_2 + 1$ to $\tau = T_3$ having the length $L_3 = T_3 - T_2$.

The observations in the estimation window can be expressed as the following regression system of the market model (II.3),

(II.5) $$\mathbf{R}_i = \mathbf{X}_i \boldsymbol{\theta}_i + \boldsymbol{\varepsilon}_i$$

where:

$$\mathbf{R}_i = \left[R_{iT_0+1} \Lambda \ R_{iT_1} \right]' \text{ is an } (L_1 \times 1) \text{ vector of estimation window returns,}$$

$$\mathbf{X}_i = \left[\iota \ \mathbf{R}_m \right] \text{ is an } (L_1 \times 2) \text{ matrix with a vector of ones in the first column,}$$

$$\mathbf{R}_m = \left[R_{mT_0+1} \Lambda \ R_{mT_1} \right]' \text{ is the vector of market return observations and}$$

$$\boldsymbol{\theta}_i = \left[\alpha_i \ \beta_i \right]' \text{ is the } (2 \times 1) \text{ parameter vector.}$$

A subscript *i* for $\mathbf{X}$ is included since the estimation window may have timing that is specific to firm *i*. Thus, using OLS estimation, the parameters of the model are

$$\hat{\boldsymbol{\theta}}_i = \left(\mathbf{X}_i' \mathbf{X}_i \right)^{-1} \mathbf{X}_i' \mathbf{R}_i$$

$$\hat{\sigma}_{\varepsilon_i}^2 = \frac{1}{L_1 - 2} \hat{\boldsymbol{\varepsilon}}_i' \hat{\boldsymbol{\varepsilon}}_i$$

(II.6)

$$\hat{\boldsymbol{\varepsilon}}_i = \mathbf{R}_i - \mathbf{X}_i \hat{\boldsymbol{\theta}}_i$$

$$\mathrm{Var}\left[\hat{\boldsymbol{\theta}}_i \right] = \left(\mathbf{X}_i' \mathbf{X}_i \right)^{-1} \sigma_{\varepsilon_i}^2.$$

It is important to note that a less restrictive form of the market model exists when the assumption $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{jt}) = 0$ is not made. This implies that along with systematic movements with the market, additional co-movements between securities can exist from effects beyond the market (e.g., industry effects). In this case, the market model is an economic model as economic intuition, in part, is used to describe the covariation of returns between different securities. However, by departing from these assumptions, a different estimation technique other than OLS, such as generalized least squares (GLS), should be used to maintain efficiency.

1.5.2 *The Capital Asset Pricing Model (CAPM)*

Based on Markowitz's (1959) groundwork that was further developed by Sharpe (1964) and Lintner (1965), the CAPM became widely used as a benchmark model in event studies in the 1970's. However, in the last decades, deviations from the CAPM have been discovered, supported by the mass of literature published on anomalies, and casting doubt on the validity of the restrictions it imposes. Yet there is much controversy about how the evidence against CAPM should be interpreted as common

arguments include that the evidence against the CAPM is overstated due to mis-measurement of the market portfolio, data-snooping and sample-selection bias. Meanwhile, multifactor models that include additional sources of risk such as the Fama French (1993) three-factor model and Carhart's (1997) four-factor model have become increasingly popular as it is often argued that CAPM does not incorporate all of the proper measures of risk. Despite all of the debate, the CAPM remains a widely used tool in finance. The remainder of this section on the CAPM focuses on defining the model followed by its assumptions and econometric estimation, which is applied in the empirical portion of the paper.

The CAPM is an economic model is described as an equilibrium theory in which the expected return of an asset is a linear function of its covariance of the return of the market portfolio. An important feature of CAPM is that it quantifies a relationship between risk and return. More specifically, the CAPM supports the notion that risky investments generally yield higher returns than investments free of risk. These higher returns can be thought of as a reward for bearing additional risk.

The CAPM is based on the principle that investors will optimally hold a mean-variance efficient portfolio, a portfolio with the highest expected return for a specified level of variance. Additionally, the CAPM has ten underlying assumptions which reduce the frictions to the movements of stock prices:

1. *No transaction costs.* There is no cost involved in buying or selling assets.

2. *Assets are infinitely divisible.* Investors can take any position in an investment any buy any fraction or value of a stock.

3. *No personal income tax.* The investor is indifferent to the form of the return (dividends or capital gains).

4. *Perfect competition.* No single investor can affect the price of a stock by an individual action. Prices are determined by the aggregate of the actions of all investors.

5. *Investors base their decisions solely on the standard deviations and expected values of the returns on their portfolios.* This is the fundamental idea behind the CAPM's stock selection framework.

6. *Unlimited short sales.* There is no limit of the number of shares that any investor can sell short.

7. *Unlimited lending and borrowing at the riskless rate.* The investor can borrow or sell any amount of funds at the interest rate equal to the rate for riskless securities.

8. *All investors are assumed to define the identical under consideration identically.* This assumption, along with assumption nine, concerns homogeneity of expectations.

9. *All investors are assumed to have identical expectations.* These expectations are based only upon expected returns, variance of returns and correlation structure between all pairs of stocks.

10. *All assets are marketable.* All assets, including human capital, can be purchased and sold on the market.

With r_f representing the return on the risk-free asset, the Sharpe-Lintner CAPM model for the expected return on asset *i* is

(II.7)
$$\mathrm{E}[R_i] - r_f = \beta_i \left(\mathrm{E}[R_m] - r_f \right)$$

(II.8)
$$\beta_i = \frac{\mathrm{Cov}[R_i, R_m]}{\mathrm{Var}[R_m]}.$$

Here, β_i is the index of systematic risk, the part of the variance of returns that cannot be diversified away. From (II.7), it is evident that nonsystematic risk, which can be diversified away, plays no role in determining the expected return. Intuition follows that if the investor can eliminate all unsystematic risk through diversification, then there is no reason why there should be any return for bearing it. Thus, the investor is rewarded only for bearing systematic risk, which is linearly related to the expected return.

The CAPM can also be applied to portfolios based on the fact that return on any portfolio is defined as a linear combination of the returns on the individual assets held in the portfolio so that

(II.9)
$$R_p = \sum_{i=1}^{N} X_i R_i$$

where:

X_i is the fraction of the portfolio held in asset *i* and

N is the number of stocks contained in the portfolio,

which is subject to the constraint

(II.10)
$$\sum_{i=1}^{N} X_i = 1.$$

Similarly, the portfolio beta β_p is a weighted average of the betas of the individual assets β_i where the weights X_i are the fraction of the portfolio invested in each stock.

(II.11)
$$\beta_p = \sum_{i=1}^{N} X_i \beta_i$$

where:

β_p is the index of systematic risk for portfolio and

β_i is the index of systematic risk for asset *i*.

Inserting these into the Sharpe-Lintner CAPM model produces

(II.12)
$$E[R_p] - r_f = \beta_p \left(E[R_m] - r_f \right),$$

the portfolio version of CAPM that is frequently used in empirical tests such as in the CAN SLIM™ analysis in Chapter III.

The Sharpe-Lintner CAPM model has three implications that are often the subject of empirical tests. These implications include the ideas that the intercept of (II.7) is equal to zero, that β captures all of the cross-sectional variation of expected excess returns and that the market risk premium $E[R_m] - r_f$ is positive. Common applications of the CAPM consist of estimating the cost of capital, evaluating portfolio performance and event-study analysis.

Since the CAPM is a single-period model that does not include time dimensions, in order to perform econometric estimation of the CAPM over time, an assumption must be made concerning time-series behavior of returns. Therefore, it is assumed that the excess returns are i.i.d. through time and are also jointly multivariate normal.

Black, Jensen and Scholes (1972) first used the basic time series model

(II.13)
$$R_{it} - r_{ft} = \alpha_i + \beta_i \left(R_{mt} - r_{ft} \right) + e_{it}$$

to conduct an extensive time series test of the CAPM. Letting Z_i represent the return on the *i*th asset in excess of the risk-free rate so that $Z_i = R_i - r_f$, (II.13) becomes

(II.14)
$$Z_{it} = \alpha_i + \beta_i Z_{mt} + e_{it}$$

from which the beta of the equity β_i can be estimated using an OLS regression as the slope coefficient of the excess-return market model. Thus, estimating β_i is a process of regressing the realized excess returns in time period *t* for asset *i* on the left-hand side of the equation on the realized excess returns of the market portfolio on the right-hand side of the equation. Implementation of this model also requires two additional inputs: the market risk premium $R_m - r_f$ and the risk-free return r_f. Typically, for analyses performed on the U.S. market, Standard and Poor's 500 Index is used as a proxy for the market portfolio while the risk-free rate is normally approximated U.S. Treasury bill rate. In the following empirical portion of this paper which focuses on the German market, the CDAX® equity index, a reflection of the overall performance of the German equity market, and the London Inter-Bank Offered Rate (LIBOR) rate are used, respectively.

In an efficient market, when (II.14) is estimated on time series data, α_i, or α_p when applied to portfolios, should be equal to zero if the CAPM sufficiently describes returns, which is consistent with the first implication discussed above. α_p is called *Jensen's alpha* which is a portfolio performance measure defined as the difference between the actual excess returns on a portfolio in any particular holding period and the expected excess returns on that portfolio which depend on the risk-free rate r_f, level of systematic risk β and actual returns of the market portfolio (Jensen 1969). A portfolio's performance is considered to be neutral if its actual returns are equal to those predicted by the CAPM, thus if $\mathrm{E}[\alpha_p] = 0$. A superior portfolio is one that realizes returns that are greater than those implied by its level of systematic risk such that $\mathrm{E}[\alpha_p] > 0$. It follows that inferior portfolios yield returns that are smaller than those implied by its level of systematic risk, therefore $\mathrm{E}[\alpha_p] > 0$. Thus, a non-zero α_p represents the portion of the return resulting from unsystematic risk, which is unrelated to the movement of the market.

Additionally, the joint hypothesis problem introduces an alternative explanation for the existence of a non-zero α_p ;the CAPM model is inadequate and does not produce accurate expected returns. More specifically, one of the main arguments of this explanation is whether the CAPM appropriately represents the risk factors that contribute to the equity's return. Therefore, measuring portfolio performance using Jensen's alpha technique simultaneously tests the portfolio manager's ability to achieve positive abnormal returns as well as the CAPM model itself. Both explanations should be considered when attempting to interpret α_p. Regardless of which model of expected returns is used, the joint hypothesis problem is always an issue when testing market efficiency.

In order to estimate and test (II.14), it is first written as the regression system

(II.15) $$\mathbf{Z}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\, Z_{mt} + \boldsymbol{\varepsilon}_t$$

where:

$\mathbf{Z}_t$ is a *(Nx1)* vector or excess returns for *N* assets (or portfolios of assets),

$\boldsymbol{\beta}$ is the *(Nx1)* vector of betas,

Z_{mt} is the time period *t* market portfolio excess return,

$\boldsymbol{\alpha}$ is the *(Nx1)* vector of asset return intercepts and

$\boldsymbol{\varepsilon}_t$ is the *(Nx1)* vector of asset return disturbances.

It follows that

(II.16)

$$\mathrm{E}[\boldsymbol{\varepsilon}_t] = 0$$

$$\mathrm{E}[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t{'}] = \boldsymbol{\Sigma}$$

$$\mathrm{E}[Z_{mt}] = \mu_m, \qquad \mathrm{E}\left[(Z_{mt} - \mu_m)^2\right] = \sigma_m^2$$

$$\mathrm{Cov}[Z_{mt}, \boldsymbol{\varepsilon}_t] = 0.$$

Here, $\boldsymbol{\mu}$ is redefined to refer to the expected excess return. Thus, from maximum likelihood estimation, which in this case leads to the same estimators as an OLS approach, the parameters of the CAPM model are

(II.17)

$$\hat{\boldsymbol{\alpha}} = \hat{\boldsymbol{\mu}} - \hat{\boldsymbol{\beta}}\hat{\mu}_m$$

$$\hat{\boldsymbol{\beta}} = \frac{\sum_{t=1}^{T} (\mathbf{Z}_t - \hat{\boldsymbol{\mu}})(Z_{mt} - \hat{\mu}_m)}{\sum_{t=1}^{T} (Z_{mt} - \hat{\mu}_m)^2}$$

$$\hat{\boldsymbol{\Sigma}} = \frac{1}{T} \sum_{t=1}^{T} \left(\mathbf{Z}_t - \hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\beta}}Z_{mt}\right)\left(\mathbf{Z}_t - \hat{\boldsymbol{\alpha}} - \hat{\boldsymbol{\beta}}Z_{mt}\right)'$$

where :

$$\hat{\boldsymbol{\mu}} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{Z}_t \quad \text{and} \quad \hat{\mu}_m = \frac{1}{T}\sum_{t=1}^{T} Z_{mt}.$$

The maximum likelihood estimators, $Z_{m1}, Z_{m2}, ..., Z_{m3}$, which are conditional on the excess return of the market, have distributions that follow from the assumed joint nor-

mality of excess returns and the i.i.d. assumption. The inverse of the Fisher information matrix can be used to derive the variances and covariances of the estimators.

The conditional distributions of the parameters are

$$\hat{\boldsymbol{\alpha}} \sim N\left(\boldsymbol{\alpha}, \frac{1}{T}\left[1 + \frac{\hat{\mu}_m^2}{\hat{\sigma}_m^2}\right]\boldsymbol{\Sigma}\right)$$

$$\hat{\boldsymbol{\beta}} \sim N\left(\boldsymbol{\beta}, \frac{1}{T}\left[1 + \frac{1}{\hat{\sigma}_m^2}\right]\boldsymbol{\Sigma}\right)$$

(II.18) $$T\hat{\boldsymbol{\Sigma}} \sim W_N(T-2, \boldsymbol{\Sigma})$$

where :

$$\hat{\sigma}_m^2 = \frac{1}{T}\sum_{t=1}^{T}(Z_{mt} - \hat{\mu}_m)^2.$$

The notation $W_N(T-2, \boldsymbol{\Sigma})$ means that the *(NxN)* matrix $T\hat{\boldsymbol{\Sigma}}$ has a Wishart distribution with $(T-2)$ degrees of freedom and a covariance matrix $\boldsymbol{\Sigma}$. The Wishart distribution is a multivariate generalization of the chi-square distribution.

The covariance of $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\beta}}$ is

(II.19) $$\text{Cov}\left[\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}'\right] = -\frac{1}{T}\left[\frac{\hat{\mu}_m}{\hat{\sigma}_m^2}\right]\boldsymbol{\Sigma}$$

and $\hat{\boldsymbol{\Sigma}}$ is independent of both $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\beta}}$.

1.5.3 Multifactor Models

As discussed in the CAPM section, empirical evidence exists that indicates that the CAPM beta does not completely explain the cross section of expected asset returns. The presence of the many documented anomalies suggests that additional risk factors may be required to adequately produce expected return figures. Hence, as an alternative to the CAPM, different multifactor pricing models are instead often used, which attempt to capture non-market influences that cause securities to move together.

The *Arbitrage Pricing Theory* (APT) introduced by Ross (1976) is a widely used multifactor economic model that determines the expected return of an asset

based on its covariance with multiple factors, all under an assumption of an absence of asymptotic arbitrage. Hence, the APT is based on the law of one price stating that two identical items cannot sell at different prices. Unlike the CAPM, the APT does not require identification of the market portfolio.

The standard form of the multifactor model with *K* uncorrelated (orthogonal) factors can be written as

(II.20)

$$R_i = a_i + \mathbf{b}_i'\mathbf{f} + \varepsilon_i$$

$$\mathrm{E}\big[\varepsilon_i|\mathbf{f}\big] = 0$$

$$\mathrm{E}\big[\varepsilon_i^2\big] = \sigma_i^2 \le \sigma^2 < \infty \quad .$$

where:

R_i is the return on asset *i*,

a_i is the intercept of the factor model,

$\mathbf{b}_i$ is a *(Kx1)* vector of factor sensitivities,

$\mathbf{f}$ is a *(Kx1)* vector of common factor realizations and

ε_i is the disturbance term.

For a system of *N* assets,

(II.21)

$$\mathbf{R} = \mathbf{a} + \mathbf{Bf} + \boldsymbol{\varepsilon}$$

$$\mathrm{E}\big[\boldsymbol{\varepsilon}|\mathbf{f}\big] = 0$$

$$\mathrm{E}\big[\boldsymbol{\varepsilon\varepsilon}'|\mathbf{f}\big] = \boldsymbol{\Sigma}$$

where:

$\mathbf{R}$ is an *(Nx1)* vector with $\mathbf{R} = \big[R_1\ R_2 \Lambda\ R_N\big]'$,

$\mathbf{a}$ is an *(Nx1)* vector with $\mathbf{a} = \big[a_1\ a_2 \Lambda\ a_N\big]'$,

$\mathbf{B}$ is an *(NxK)* matrix with $\mathbf{B} = \big[\mathbf{b}_1\ \mathbf{b}_2 \Lambda\ \mathbf{b}_N\big]'$ and

$\boldsymbol{\varepsilon}$ is an *(Nx1)* vector with $\mathbf{R} = \big[\varepsilon_1\ \varepsilon_2 \Lambda\ \varepsilon_N\big]'$.

Furthermore, it is assumed that the factors account for the common variation in asset returns so that the disturbance term $\boldsymbol{\varepsilon}$ for well-diversified portfolios vanishes, which requires $\boldsymbol{\varepsilon}$ to be sufficiently uncorrelated across assets.

Using this structure, Ross (1976) shows that in large economies having no arbitrage

(II.22)
$$\boldsymbol{\mu} \approx \boldsymbol{\iota}\lambda_0 + \mathbf{B}\boldsymbol{\lambda}_K$$

where:

$\boldsymbol{\mu}$ is the *(Nx1)* expected return vector,

λ_0 is the model zero-beta parameter equal to the risk-free return if such an asset exists and

$\boldsymbol{\lambda}_K$ is a *(Kx1)* vector of factor risk premia.

The approximation in (II.22) does not produce directly testable results for asset returns. Hence, in order to restrict and thus, test, the model, additional structure must be imposed so that the model is exact. Several authors have approached this problem in different manners. In Connor's (1984) competitive equilibrium version of the APT, the market portfolio must be well-diversified, meaning no single asset in the economy accounts for a significant proportion of aggregate wealth, and the factors must be pervasive so that investors can diversify away idiosyncratic risk without restricting their choice of factor exposure. Alternatively, Dybvig (1985) and Grinblatt and Titman (1985) investigate the potential magnitudes of the deviations from exact factor pricing given structure on the preferences of a representative agent and conclude that, given a reasonable specification of the parameters of the economy, theoretical deviations from exact factor pricing are likely to be negligible. Additionally, Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) in combination with assumptions on the conditional distribution of returns, produces a multifactor model in which the market portfolio serves as one factor and state variables serve as additional factors. From this point on in the paper, only multifactor models with exact factor pricing will be analyzed such that

(II.23)
$$\boldsymbol{\mu} = \boldsymbol{\iota}\lambda_0 + \mathbf{B}\boldsymbol{\lambda}_K.$$

When estimating an exact factor pricing model, it is assumed that the time-series returns are i.i.d. and jointly multivariate normal. Since multifactor models do not specify the number nor the identification of the factors, the factors must first be determined, a process which will be addressed later in this section. Four versions of the exact factor pricing model exist: (1) Factors are portfolios of traded assets and a risk-free asset exists; (2) Factors are portfolios of trades assets and no risk-free asset

exists; (3) Factors are not portfolios of traded assets; and (4) Factors are portfolios of traded assets and the factor portfolios span the mean-variance frontier of risky assets. Maximum likelihood estimation can be used to estimate all four versions, which can be seen in Campbell, Lo and MacKinlay (1997). Here, only the first case will be detailed as this case is applied in the empirical section of the paper.

In this case, where the factors are traded portfolios and a risk-free asset exists, the unconstrained model, *K*-factor model expressed in excess returns is

(II.24) $$\mathbf{Z}_t = \mathbf{a} + \mathbf{B}\mathbf{Z}_{Kt} + \boldsymbol{\varepsilon}_t$$

where:

$\mathbf{Z}_t$ is an *(Nx1)* vector of excess returns for *N* assets (or portfolios of assets),

$\mathbf{B}$ is the *(NxK)* matrix of factor sensitivities,

$\mathbf{Z}_{Kt}$ is an *(Kx1)* vector of factor portfolio excess returns,

$\mathbf{a}$ is an *(Nx1)* vector of asset return intercepts,

$\boldsymbol{\varepsilon}_t$ is an *(Nx1)* vector of asset return disturbances,

$\boldsymbol{\Sigma}$ is the variance-covariance matrix of disturbances,

$\boldsymbol{\Omega}_K$ is the variance-covariance matrix of factor portfolio excess returns and

$\mathbf{O}$ is a *(KxN)* matrix of zeros.

For the unconstrained model (II.24), the maximum likelihood estimators are equivalent to the OLS estimators

$$\hat{\mathbf{a}} = \hat{\boldsymbol{\mu}} - \hat{\mathbf{B}}\hat{\boldsymbol{\mu}}_k$$

$$\hat{\mathbf{B}} = \left[\sum_{t=1}^{T}(\mathbf{Z}_t - \hat{\boldsymbol{\mu}})(\mathbf{Z}_{Kt} - \hat{\boldsymbol{\mu}}_K)'\right]\left[\sum_{t=1}^{T}(\mathbf{Z}_{Kt} - \hat{\boldsymbol{\mu}}_K)(\mathbf{Z}_{Kt} - \hat{\boldsymbol{\mu}}_K)'\right]^{-1}$$

$$\hat{\boldsymbol{\Sigma}} = \frac{1}{T}\sum_{t=1}^{T}\left(\mathbf{Z}_t - \hat{\mathbf{a}} - \hat{\mathbf{B}}\mathbf{Z}_{Kt}\right)\left(\mathbf{Z}_t - \hat{\mathbf{a}} - \hat{\mathbf{B}}\mathbf{Z}_{Kt}\right)'$$

(II.25)

where:

$$\hat{\boldsymbol{\mu}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{Z}_t \quad \text{and} \quad \hat{\boldsymbol{\mu}}_K = \frac{1}{T}\sum_{t=1}^{T}\mathbf{Z}_{Kt}.$$

For the estimators of the constrained model with **a** constrained to be zero, see Campbell, Lo and MacKinlay (1997).

Factor selection for multifactor models can be performed by using either statistical or theoretical approaches. In statistical approaches, factors are built from a comprehensive set of asset returns using either factor analysis or principal component analysis. Factor analysis aims to minimize the covariance of residual returns by estimating the factor sensitivities and then orthogonal factors, which are linear combinations of returns, so that portfolios that are perfectly correlated with the factors can be constructed. The resulting factor portfolio returns can be used in all four versions of the exact factor pricing model. The goal of principal component analysis is to reduce the number of variables while retaining without losing too much information in the covariance matrix, in other words, to reduce the dimension from N asset returns to K factors. Here, the principal components, which are orthogonal linear combinations of asset returns with maximum variance, serve as the factors. The question remains open which approach, factor analysis or principal components, is optimal for constructing the model factor. Campbell, Lo and MacKinlay (1997) discuss this issue further and provide deeper mathematical insight into both approaches as do Härdle and Simar (2003).

Theoretical approaches specify factors based on arguments that the factors capture economy-wide systematic risks. Under this approach, factors can include macroeconomic and financial market variables or firm characteristics which explain differential sensitivity to systematic risks. Many empirical studies of multifactor models exist, especially those on theoretical approaches, including that of Chen, Roll and Ross (1986) who used intuitive analysis and empirical investigation to develop a five-factor macroeconomic model. They selected factors under the logic that the factors should explain changes in the discount rate used to discount future expected cash flows and forces which influence expected cash flows themselves. In their model, the factors include the yield spread between long and short interest rates for U.S. government bonds, expected inflation, unexpected inflation, industrial production growth and the yield spread between high and low grade corporate bonds. On the firm characteristic and financial variable side of theoretical approaches, it has been discovered that variables such as market value of equity, price-to-earnings ratio and book-to-market equity, when implemented in combination with a broad-based market portfolio, can effectively explain the cross-section of returns. As previously mentioned in the CAPM section, well-known models of this sort include the Fama French (1993) three-factor model and Carhart's (1997) four-factor model.

While multifactor models are often capable of providing more explanatory power than the single-factor CAPM, their apparent attractiveness should be approached with caution. Since the factors are chosen to fit existing data, multifactor

models may overfit the data because of the data-snooping bias. Additionally, multi-factor models may capture empirical regularities that are due to market inefficiencies of investor irrationality.

Chapter III
Empirical Analysis

1.1 The CAN SLIM™ System

CAN SLIM™ is a technique of screening, purchasing and selling individual stocks, which was developed by William O'Neil, a well-known American investment analyst, mutual fund creator and founder of the "Investor's Business Daily" newspaper. The CAN SLIM™ method has attracted much attention in the U.S. and boasts a 704.9% return from 1998 – 2003 on its website compared to the 14.6% return of the S&P 500 during the same period[1].

The CAN SLIM™ system is based on both fundamental and technical analysis of stocks and the market environment, focusing on finding exceptional stocks with extremely high-growth potential. O'Neil developed the CAN SLIM™ method by analyzing the 500 U.S. stocks that have increased the most in value from 1953 – 1993 by looking for common observable characteristics shared by these stocks before their prices skyrocketed. From this analysis, he determined that these so-called *breakout stocks*, share seven observable characteristics, each which is represented by a letter of the CAN SLIM™ acronym:

C - *Current quarterly earnings per share.* Target stocks with increases of at least 20% in the current quarterly earnings report, preferably those whose earnings growth has accelerated in the past three quarters.

A - *Annual earnings per share (EPS).* Look for stocks with consistent growth over the past five years, averaging at least 20% annual EPS growth with no single year being down.

N - *New.* Buy stocks of companies with new products, new management or other positive significant changes in their industry conditions. Additionally, buy stocks as they reach new price highs and do not buy cheap stocks.

S - *Supply and demand.* Choose companies with small market capitalization with a small or reasonable number of outstanding shares, restricting supply so that an increase in demand will result in prices being driven up. Smaller firms are more likely to have innovative, entrepreneurial management teams.

L - *Leaders.* Buy market leaders and avoid laggards. Identify the sector and industry groups with the highest performance and then focus on the best-

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[1] Source: CAN SLIM™ website (www.canslim.net) and the AAII Journal, January 2004.

performing stocks within that industry. Concentrate on relative strength (or "momentum").

I - *Institutional sponsorship.* Select stocks with a few institutional sponsors with good performance records but avoid "overowned" stocks.

M - *Market.* The direction of the market is the most deterministic factor of stock prices. Study the general market trend to help avoid losses in bear markets an to be an early-mover at the first signs of a new bull market.

Over 600 institutional investors in the U.S. currently use O'Neil's investment and research services. However, the CAN SLIM™ method also targets the individual American investor, with its methods broken down into easy-to-understand terminology which is presented in books and seminars, on websites and through investment services. O'Neil embraces the American entrepreneurial spirit, himself being a self-made success story, as he stands by his belief that, "Anyone can do it. You can do it."

Despite the ability of the CAN SLIM™ method to be presented in a simplistic manner, its fundamentals are deeply rooted in finance theory and involve the complex issue of market efficiency. As discussed in the first section, a vast number of journal articles have been written on market efficiency, trying to document the existence of inefficiencies that one can use to exploit the market and make abnormal profits. The success of CAN SLIM™ seems to indicate that certain inefficiencies exist although there is a lack of quantitative research on the CAN SLIM™ method as a whole. However, individual studies of different market conditions and anomalies, including the momentum effect, size effect and E/P ratios, have revealed that abnormal returns can be predicted to some extent, providing some academic basis for CAN SLIM™'s apparent success. Furthermore, there exists a lack of analysis of the CAN SLIM™ approach outside of the U.S. investment universe, a hole that this paper attempts to partially fill.

To my knowledge, apart from this paper, the effectiveness of CAN SLIM™ in the German market has not yet been evaluated. However, there seems to be much preliminary evidence for the potential success of CAN SLIM™ in Germany in the form of several published papers. Notably, Jegadeesh and Titman (1993) confirm the existence of momentum effects which are strongest among small-cap stocks. Additionally, studies by Fama and French (1992), Lakonishok, Shleifer and Vishny (1994) and Davis (1994) relate the predictability of future returns to the relative sizes of the current stock prices and current values of earnings per share. While these previously mentioned papers do not specifically focus on Germany, Haugen and Baker (1996) provide an important link as they find that determinants of expected stock returns are strikingly common across major international equity markets, including Germany's.

However, Schiereck, De Bondt and Weber (1999) provide the most compelling evidence that CAN SLIM™ may succeed in the German market. They performed a momentum study in the German market with data from 1961-91 and found that long/short momentum strategies seem to be profitable, beating a passive approach of investing in the market index, no matter what the state of the economy. Moreover, Schiereck, De Bondt and Weber do not attribute these abnormal returns to misaccounting for risk, but rather to inefficient markets. They also find that the size of the abnormal returns is substantial, even after accounting for transaction costs. Rouwenhorst (1998), in his more general international approach, also finds strong evidence of medium-term return continuation, which is negatively related to firm size, in his analysis of twelve European markets. Furthermore, he concludes that this outcome is inconsistent with the EMH. It is interesting that both of these papers emphasize that the results of their respective momentum studies are strikingly similar to the results of the momentum studies performed on U.S. markets, stressing that the dynamics of stock prices in Frankfurt and New York seem to be correlated. This finding hints at possible common factors of price momentum or aspects of behavioral finance.

The remainder of this paper is an empirical study of a modified CAN SLIM™ approach applied to the German equity market. In the search for the existence of abnormal profits, the factors of the CAN SLIM™ model and their relevancy and applicability to the German market are first evaluated. Then, historical data from the German market is subjected to a CAN SLIM™ stock screen to test for abnormal profits, which, if found, would signal that the CAN SLIM™ approach has potential to be successfully implemented on an ongoing basis in Germany. However, the results from this analysis are not free from the typical problems of an event study, including potential biases and the joint hypothesis problem which are both explained in the first section, making any profits that might be discovered controversial as to whether they really exist.

1.2 CAN SLIM™ Analysis of the German Market

1.2.1 Investment Universe

In order to accurately partake in a thorough analysis of the German market, it is necessary to define a broad investment universe consisting of a wide representation of securities that is fully reflective of the performance of the overall German equity market. Thus, data from companies listed on the CDAX® index were used in the following analysis, which covers all German shares admitted to the Prime Standard and General Standard segments of the Frankfurt Stock Exchange. Since the CDAX® constituents frequently change, the 683 constituents listed on the CDAX® as of May 18, 2005 (see Appendix 1) represent the investment universe referred to throughout this analysis. Although CDAX® historical data dates back to the beginning of 1970,

this analysis uses stock data from 1980 - 2005 since some segments of data, such as earnings per share and cash flow per share, are only consistently available beginning in 1980. Additionally, all data used is based on prices from floor trading at the Frankfurt Stock Exchange (Frankfurter Wertpapierbörse) as opposed to Deutsche Börse's Xetra electronic trading system prices. Datastream and the Worldscope database are the sources of all data used in this paper. Lastly, the software program EViews was used to perform the econometric analysis in this paper.

1.2.2 Initial Screening of CAN SLIM™ Factors

The purpose of the first part of this analysis is to determine the relevancy of two of the main CAN SLIM™ factors, earnings growth and price momentum, and to test for and, when possible, quantify, the factors' relationship with respect to stock price in our investment universe. The first task focused on examining EPS data for all 683 CDAX® stocks since the first two criteria of the CAN SLIM™ system focus on selecting stocks based on quarterly and annual earnings. However, our German investment universe differs from the American investment universe in which the original CAN SLIM™ analysis was performed, mainly due to different reporting standards.

In the U.S., the GAAP (*Generally Accepted Accounting Principles*) standard for reporting earnings results in EPS data that is more accurate than the EPS data for German companies. The reason for the difference is that the GAAP stipulate exactly how EPS figures should be calculated, leaving less room for companies to smooth their earnings over successive periods so that they can manipulate the market perception of their firms' performance. In Germany, the HGB (*Handelsgesetzbuch*) guidelines for reporting earnings are not as strict and allow companies to create earnings that look better, meaning higher and smoother, to investors, especially in periods when there are losses and high earnings volatility. With an absence of strict accounting regulations, some managers may attempt to make financial performance look healthier in this way (Ciccone 2002). For this reason, EPS data for the 683 CDAX® companies should not be taken at face value, as it is not a reliable factor on which to partially base our CAN SLIM™ selection of stocks. Instead, *cash flow per share* (CFS) data is used in our analysis as a more accurate measure of a firm's true financial state.

In order to measure market effects in stock price movements, an equally weighted *benchmark* (BM) index is created from the historical returns of the 683 CDAX® constituents from 1980 - 2005. With the CDAX® constituents changing frequently, this technique of calculating a BM index provides a true representation of the historical returns of the 683 stocks against which the performance of a CAN SLIM™ portfolio can be measured. Using this self-created BM partially alleviates a portion of the survivorship bias since the BM is an exact index of the average performance of the 683 constituents and does not include any extraneous return data. However, an

unavoidable facet of the survivorship bias still exists, due to the unavailability of data from former CDAX® constituents, since the evaluation and selection universe for choosing CAN SLIM™ stocks includes only these 683 stocks which have successfully survived until today. Thus, some potentially "bad choices" have already been eliminated from potential CAN SLIM™ selection. Likewise, using this equally weighted BM removes any large-cap bias, which is very important in a CAN SLIM™ analysis targeting small-cap stocks. This equal-weighting technique allows for superior or inferior performance by small-cap companies to be adequately reflected in the BM index and, furthermore, provides an accurate basis of comparison for our selected CAN SLIM™ stocks.

Figure III-1 plots this self-created BM index along with the CDAX® index from 1979 – 2005. The solid line represents the natural log difference of the BM and the CDAX® return indices, measured on the right y-axis, in percent difference. The indices appear to closely mirror each other through time. Thus, it is clear that using the self-created BM as opposed to the CDAX® index as a benchmark in this CAN SLIM™ analysis will not drastically affect the results.

Figure III-1: BM and CDAX® Return Indices. Left Y-axis for BM and CDAX, Right Y-axis for natural logarithm.

Next, an *ordinary least squares* (OLS) cross-sectional regression is performed to examine the relationship between CFS growth and stock price. The model

(III.1)
$$\ln\left(\frac{P_{it+2}}{P_{it+1}}\right) - \ln\left(\frac{BM_{t+2}}{BM_{t+1}}\right) = \alpha + \beta\left(\frac{CFS_{it} - CFS_{it-1}}{P_{it-1}}\right) + \varepsilon_{it}$$

where:

P_{it} is the price of security *i* in year *t*,

BM_{t+2} is the self-created benchmark for year *t+2*,

CFS_{it} is the cash flow per share of security *i* in year *t* and

ε_{it} is the unexplained component of stock *i's* return in year *t*

is used to estimate the parameters α and β. Thus, this model regresses the market-adjusted natural log returns on scaled CFS growth. It is assumed that the CFS data for year *t* is announced in or by April of year *t+1*, after which the stock is then purchased and held for one year until April of year *t+2*. In order to make CFS growth comparable for different companies, it is necessary to scale the amount of change in CFS by dividing by the price per share at the end of the previous year based on Chou's (1975) method. It is important to note that this model assumes a CAPM β equal to one for all 683 stocks so that subtracting the natural log difference of the BM from the natural log return in identical periods removes any market effects. Due to the unavailability of quarterly CFS data, all available annual historical CFS data[2] from 1980 to 2003 was used. All price data is taken from April 30th of each year to correspond with earnings announcements.

This regression[3] of 4,904 observations yields an adjusted $R^2 = 0.000045$, revealing no discernable relationship between CFS growth and returns (see Appendix 2 for regression tables). Even trimming the normalized data to +/- 3 standard deviations does not substantially change the regression results. The absence of a relationship between the two variables in equation (III.1) can be also witnessed in the scatter plot in Figure III-2 as there is an apparent clumping of CFS growth data around zero.

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[2] The CFS data represents the sum of net income and all non-cash charges or credits and includes depreciation, amortization of intangibles and deferred taxes but excludes extraordinary items and changes in working capital, divided by the number of outstanding shares.

[3] Due to highly suspect CFS data, the 2001 and 2002 observations for Saltus Technology AG were omitted from all regressions in this paper involving CFS data.

Figure III-2: Scatter plot of Data Used in Regression of Equation (III.1)
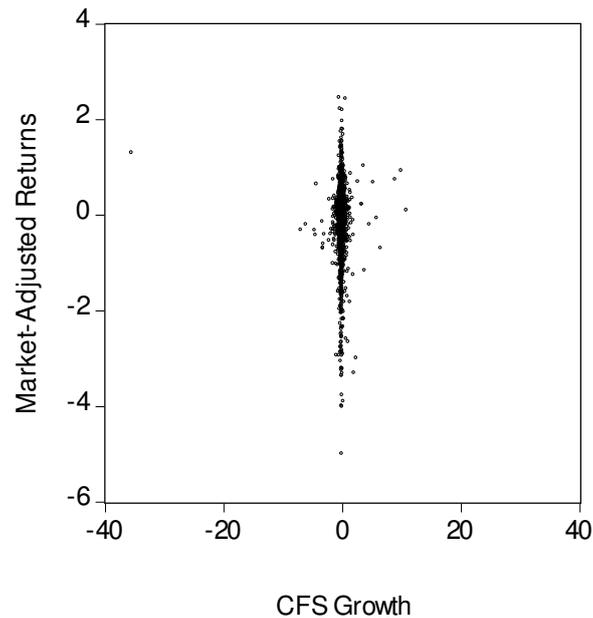
Since data from the entire population of 683 CDAX® stocks fails to provide any hint of a relationship between CFS growth and returns, the next step in the analysis is aimed at finding tail dependence in stocks having the highest and lowest CFS growth figures. First, all 683 stocks are ranked for each year *t* from 1981 – 2003 based on their scaled CFS growth figures. For each year, portfolios of the highest and lowest 10% of stocks are formed based on the CFS growth rankings. Stocks with missing data values for a particular year are omitted from the analysis for that year. Appendix 3 displays by year the number of CDAX® constituents with available price and CFS data. Next, equally weighted averages of the *t+2* year discrete returns of the Top 10% and Bottom 10% portfolios are calculated and compared to the equally weighted BM index as illustrated in Figure III-3. Additionally, Figure III-3 shows the returns from a Long/Short portfolio created from longing the Top 10% portfolio and shorting the Bottom 10% portfolio.

Figure III-3: Same-Year Returns of CFS Growth-Ranked Portfolios
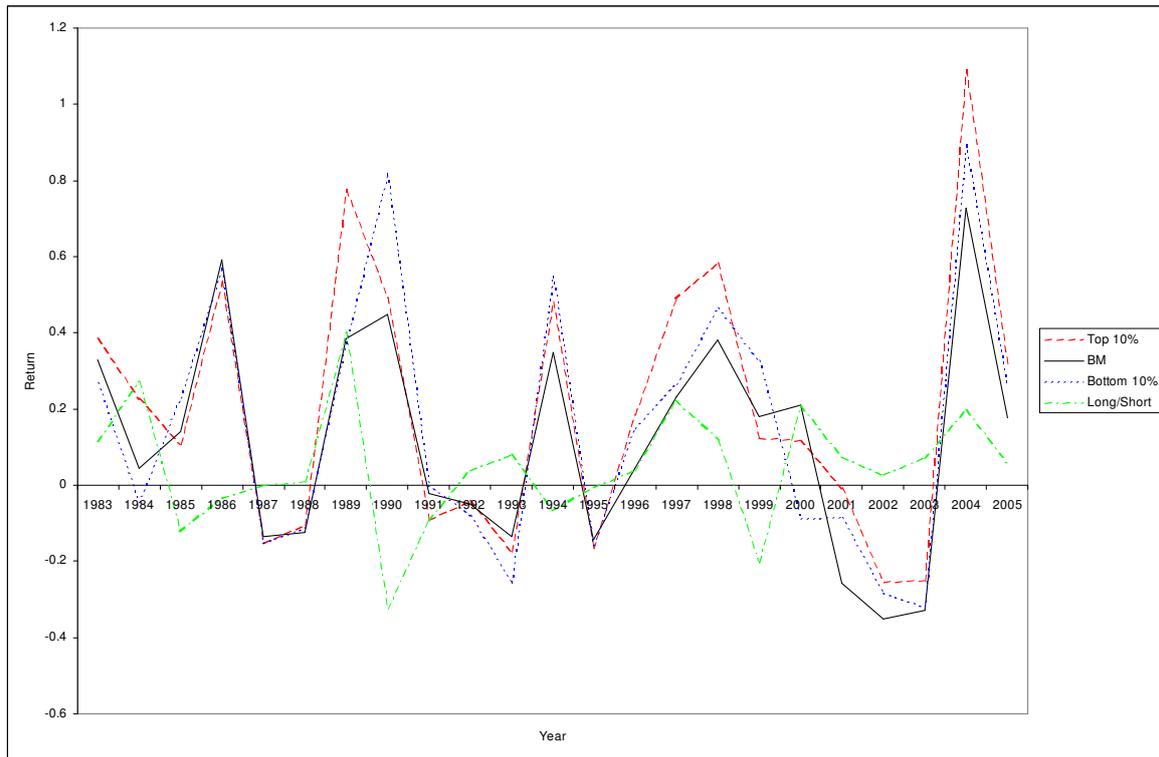
The associated t-statistics, which test whether the returns are reliably different that zero, are reported in Table III-1. The Top 10% portfolio outperforms the BM by a mean of 8.60% with a t-statistic equal to 2.99, signaling that portfolios formed from the upper decile of each year's scaled CFS growth figures have a strong tendency to produce abnormal returns in year *t+2*. This positive performance of the Top 10% portfolio is an important indication that helps to substantiate the CAN SLIM™ stock screening performed later in the next section of this paper.

However, the Bottom 10% portfolio outperforms the mean by 3.87% with a t-statistic 1.42, failing to reveal any significant relationship between this bottom decile portfolio and the *t+2* year returns.   The fact that the Bottom 10% portfolio outper-forms the mean suggests that selecting short portfolios based on CFS growth as the sole criterion will not result in positive returns to the investor.

Table III-1:   t-statistics for Same-Year Returns of CFS Growth-Ranked Portfolios

	mean return (%)	standard deviation	t-statistic	p-value
Top 10% - BM	8.60	13.78	2.99	0.0007
Bottom 10% - BM	3.87	13.09	1.42	0.1702
Long/Short	4.73	15.70	1.44	0.1626

Price momentum, a second main CAN SLIM™ factor, also known as relative strength, is based on the idea that returns are predictable and will continue in the direction of the current trend for future periods. Under this assumption, returns in periods t and t-1 are positively correlated over time. In an attempt to quantify this relationship, a serial OLS regression is performed as a general test of dependence of returns on past returns using the model

$$\text{(III.2)} \qquad \ln\left(\frac{P_{it}}{P_{it\text{-}1}}\right) - \ln\left(\frac{BM_t}{BM_{t\text{-}1}}\right) = \alpha + \beta\left(\ln\left(\frac{P_{it\text{-}1}}{P_{it\text{-}2}}\right) - \ln\left(\frac{BM_{t\text{-}1}}{BM_{t\text{-}2}}\right)\right) + \varepsilon_{it}\,.$$

Using all available market-adjusted price data from the 683 CDAX® constituents from t = 1981 – 2005, 6,360 observations are regressed to produce an adjusted R^2 = 0.034236. Based on this R^2 value as well as β = 0.176175 (significant at 99%) and the scatter plot and regression line depicted in Figure III-4, a positive relationship exists between today's and yesterday's returns for the general population of data from all 683 stocks. It is also evident from Figure III-4 that, in addition to the visual trend that is confirmed by the regression, there is a large cluster of data points around the zero points of both axes, signaling that there are many near-BM market-adjusted returns. Judging from this apparent lack of extreme data, it might be difficult to select stocks with extraordinarily high or low returns that satisfy the CAN SLIM™ criteria.

Figure III-4: Price Momentum Regression using Equation (III.2)

Market-adjusted Returns at t-1
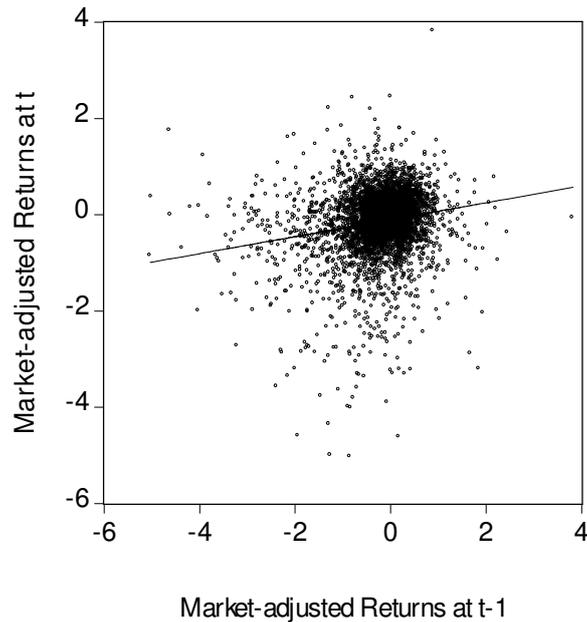
Performing this regression again on data that was normalized and trimmed to +/-3 standard deviations reveals even less of a trend in the cross-sectional data, yielding even a smaller $R^2 = 0.025418$. The decrease in the R^2 value resulting from trimming the data indicates that the tail data may be more predictable with respect to relative strength. Therefore, the results of these price momentum regressions suggest that adopting a price momentum strategy for those stocks with extremely high or low returns may be able to be exploited to produce abnormal returns. The following momentum study examines this idea in detail.

Figure III-5: Price Momentum Strategy Implementation
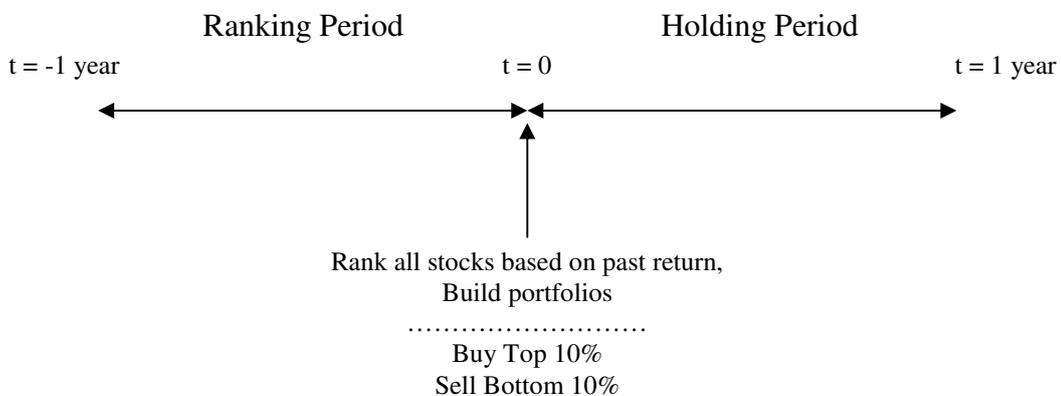
Subsequently, a price momentum strategy similar to Jegadeesh and Titman's (1993) is implemented in the CDAX® investment universe to test for the existence of abnormal returns using information contained in the tails of the previous year's return distribution. In a price momentum strategy, an investor is able to make decisions about which stocks to buy or sell based on historical data, employing both long and short strategies. Figure III-5 illustrates the typical scheme of a price momentum study, which is next applied to our investment universe. First, for each year from 1980 - 2005, all 683 CDAX® stocks with available data are ranked based on their discrete returns from the past year (*t = -1 year)*. As previously mentioned, all annual price data is from April 30th of each year, which corresponds to the *t = 0* date for each year's ranking. Portfolios of the Top 10% (winners) and Bottom 10% (losers) ranked stocks are then formed for each year. These portfolios are then held for one year (*t = 1 year)* after which an equally weighted average of the discrete returns of the Top 10% and Bottom 10% portfolios is calculated. Figure III-6 is a plot of the returns of the Top 10% and Bottom 10% portfolios in relation to the equally weighted BM return as well as the returns of a Long/Short portfolio created from longing the Top 10% portfolio and shorting the Bottom 10% portfolio.

Figure III-6:   Price Momentum Returns
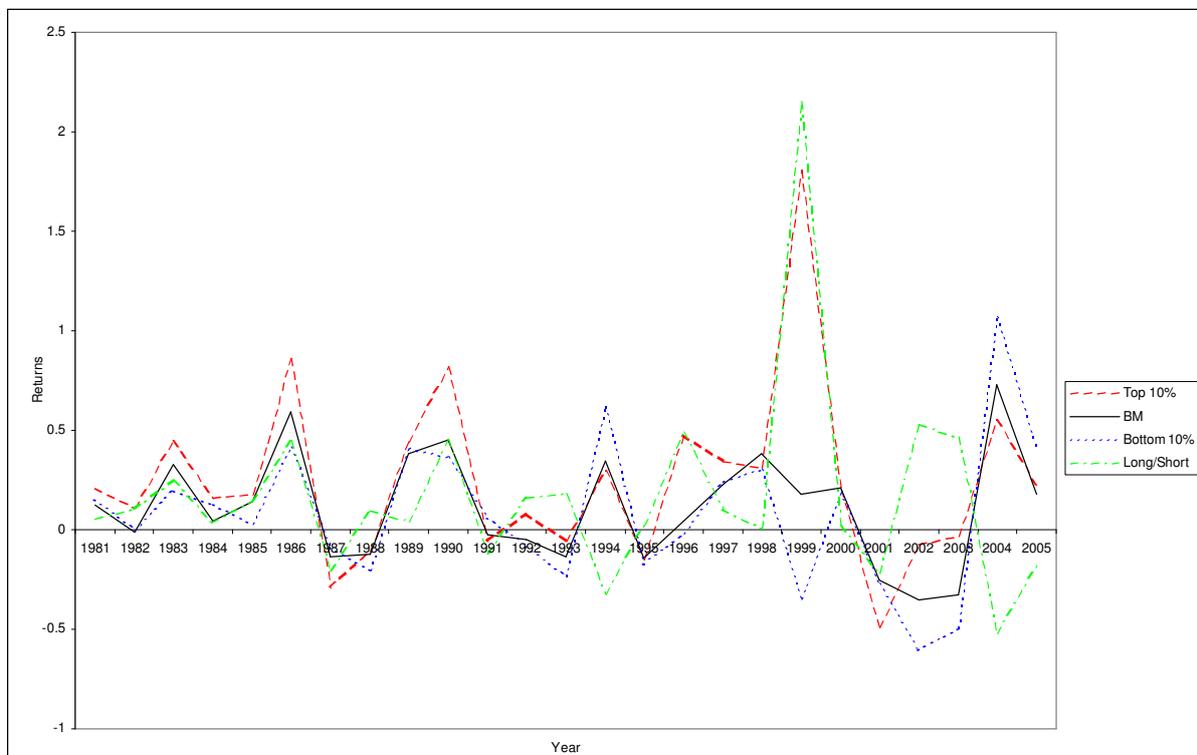
The t-statistics for this price momentum analysis are displayed in Table III-2. Here, the price momentum strategy for selecting stocks looks promising as the Top

10% and Long/Short portfolios outperform the BM by 13.91% and 16.80%, respectively, and are accompanied by t-statistics of 1.99 and 1.72. Implementing the short strategy alone, however, seems to have a smaller potential for profitability as the Bottom 10% portfolio underperforms the BM by 2.89% with a t-statistic of -0.84. Although the returns from the Top 10% and Long/Short portfolios are high, so is the volatility, which is characteristic to momentum investment strategies.

Table III-2:   t-statistics for Price Momentum Returns

	mean return (%)	standard deviation	t-statistic	p-value
Top 10% - BM	13.91	34.86	1.99	0.0575
Bottom 10% - BM	-2.89	17.11	-0.84	0.4085
Long/Short	16.80	48.84	1.72	0.0983

To further analyze the effectiveness of momentum strategies, the Top 10%, Bottom 10% and Long/Short portfolios are next evaluated using a modified version of the CAPM (III.3) and the market model (III.4)

(III.3)
$$R_p - r_f = \alpha + \beta\,(R_{BM} - r_f) + \varepsilon$$

(III.4)
$$R_p = \alpha + \beta\,R_{BM} + \varepsilon$$

where:

r_f is the 1-year LIBOR,

R_p is the return on the portfolio (Top 10%, Bottom 10%, Long/Short),

R_{BM} is the return on the equally weighted BM portfolio and

ε is the unexplained component of the portfolio's (excess) return.

The purpose of this procedure is aimed at finding significant positive (Top 10% and Long/Short) and negative (Bottom 10%) α's, which represent the portion of the portfolio's return that is unexplained by the BM market portfolio's performance. Thus, the existence of a positive α means that the portfolio produces better than expected risk-adjusted returns. In effect, these regressions test the weak form of the EMH. If one can achieve abnormal returns by selecting a portfolio based on historical price momentum information, then market inefficiency exists.

Each portfolio (Top 10%, Bottom 10% and Long/Short) is regressed on the equally weighted BM portfolio using both models for a total of six regressions. In all

regressions, White's heteroskedasticity consistent covariance matrix estimator is used to provide correct estimates of the coefficient covariances in the presence of heteroskedasticity of unknown form.

The significant (at the 90% level) information obtained from these regressions is that the Top 10% portfolio produces $\alpha = 13.8\%$ using the market model and 13.6% using the CAPM. Additionally, the Long/Short portfolio produces $\alpha = 18.3\%$ using the market model. All other α's are found to be insignificant. This information points to market inefficiencies in the German market that can be exploited by employing a long strategy based on price momentum.

Lastly, an attempt is made to explain the performance of the CAN SLIM™ Long/Short portfolios, which are selected based on price momentum criteria, by the performance of three different Credit Suisse First Boston (CSFB)/Tremont hedge fund indices: the Composite Hedge Fund index, the Equity Market Neutral Hedge index and the Long/Short Hedge index. While, as shown earlier in this section, the CAN SLIM™ Long/Short momentum portfolios significantly outperform the BM, the returns of the CFS growth Long/Short portfolios are not significant, as indicated by the small t-statistic, and therefore are not evaluated in this part of the analysis.

The motivation behind this portion of the paper centers on the idea that long/short approaches are typical hedge fund approaches. Therefore, it is logical to hypothesize that a relationship between the performance of the CAN SLIM™ Long/Short portfolios and different hedge fund indices exists. In order to test for such a relationship, a regression is performed on the following excess return model,

(III.5) $$R_{L/S} - r_f = \alpha + \beta \left(R_{HF} - r_f \right) + \varepsilon$$

where:

r_f is the 1-year LIBOR,

$R_{L/S}$ is discrete return on the Long/Short momentum portfolio,

R_{HF} is the natural log of the holding period return on the specified hedge fund index (Composite, Equity Market Neutral or Long/Short) in euro,

ε is the unexplained component of the L/S portfolio's excess return.

Analogous to the CAPM, this model employs excess returns, regressing excess Long/Short portfolio returns on excess returns of the hedge fund indices. The identi-

cal Long/Short momentum portfolios built and evaluated in the previous price momentum analysis are also used here.

CSFB/Tremont's hedge fund indices[4] are industry standards in hedge fund benchmarking and research. Collaboratively, CSFB and Tremont produce an asset-weighted index of general hedge fund performance, the CSFB/Tremont Hedge Fund Index, which is broken into ten sub-indices, each representative of a different hedge fund investment style. The CSFB/Tremont Hedge Fund Index, here referred to as the Composite Index, measures the performance of over 400 funds across the ten style-based sectors, each having a minimum of $50 million in assets under management, a minimum one-year track record and current audited financial statements.

The Equity Market Neutral Index and the Long/Short Equity Index are two of the sub-indices that employ long/short strategies similar to that of the Long/Short momentum portfolios. The Equity Market Neutral Index composes 4.6% of the Composite index and represents an investment strategy designed to exploit equity market inefficiencies with equally matched long and short equity portfolios within a single country. These portfolios are designed to be either beta or currency neutral, or both, and often apply leverage to enhance returns. The Long/Short Equity Index composes 25.8% of the Composite index and encompasses a directional strategy involving both long and short equity-oriented investing. Here, the objective is not to be market neutral but instead to allow managers to shift portfolios from value to growth, small- to medium- to large-cap stocks and from a net long position to a net short position. Futures and options are often used to hedge, and these portfolios tend to be substantially more concentrated than portfolios of traditional stock funds.

Only discrete returns of the three CSFB/Tremont indices are available from Datastream, so the indices are first reconstructed from the returns and then converted from dollars to euro. Finally, the natural log of the holding period return of each index is calculated, thus representing the R_{HF} term in (III.5). Each of the three regressions using (III.5) is performed using the eleven annual observations of Long/Short momentum portfolio returns from April 30th of each year from 1995 – 2005 and the corresponding R_{HF} values of the respective CSFB/Tremont Composite, Equity Market Neutral and Long/Short Equity indices. None of the regressions yield significant β's, thus the hypothesis of an existing relationship between the excess returns of the Long/Short momentum portfolios and the excess returns of the three CSFB/Tremont hedge fund indices is rejected in each case. For the purposes of this CAN SLIM™ analysis, the absence of any relationship is promising since it suggests that the CSFB/Tremont hedge funds have factors other than momentum influencing their excess returns. This finding hints that long/short portfolio selection based on the

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[4] All information about the CSFB/Tremont hedge fund indices was taken directly from the CSFB/Tremont website *www.hedgeindex.com*.

CAN SLIM™ approach is unique from traditional long/short hedge fund approaches and, if found to be successful, CAN SLIM™ might be able to exploit previously untapped inefficiencies within the German market.

1.2.3 CAN SLIM™ Preliminary Screening

While the previous section confirms that two of the main CAN SLIM™ factors, CFS growth (substituted for EPS growth) and relative strength, are relevant in the German market, at least on the long side, this section goes one step further by implementing a series of stock screens in the CDAX® investment universe based on these factors. Despite the lack of encouraging short-side results in the last section, this preliminary CAN SLIM™ screening is a "mirrored" CAN SLIM™ approach meaning in addition to following O'Neils long side selection criteria, an opposite approach is applied to the short side.

The first screen is designed to capture CAN SLIM™'s *"A"* (annual earnings per share growth) factor, which in this analysis, as previously explained, is substituted with CFS growth data. For each year on the long side, the last four absolute CFS values must be positive (i.e., when choosing stocks on April 30th in year t then $CFS_{t-1}, CFS_{t-2}, CFS_{t-3}, CFS_{t-4} > 0$) or else the stock is eliminated from the selection list from that year. For the remaining stocks, the average CFS growth over the past three years is calculated and any stocks having less than 20% average annual CFS growth are filtered out for that year.

Figure III-7: Returns of Long and Short Portfolios after the Annual CFS Growth Screen
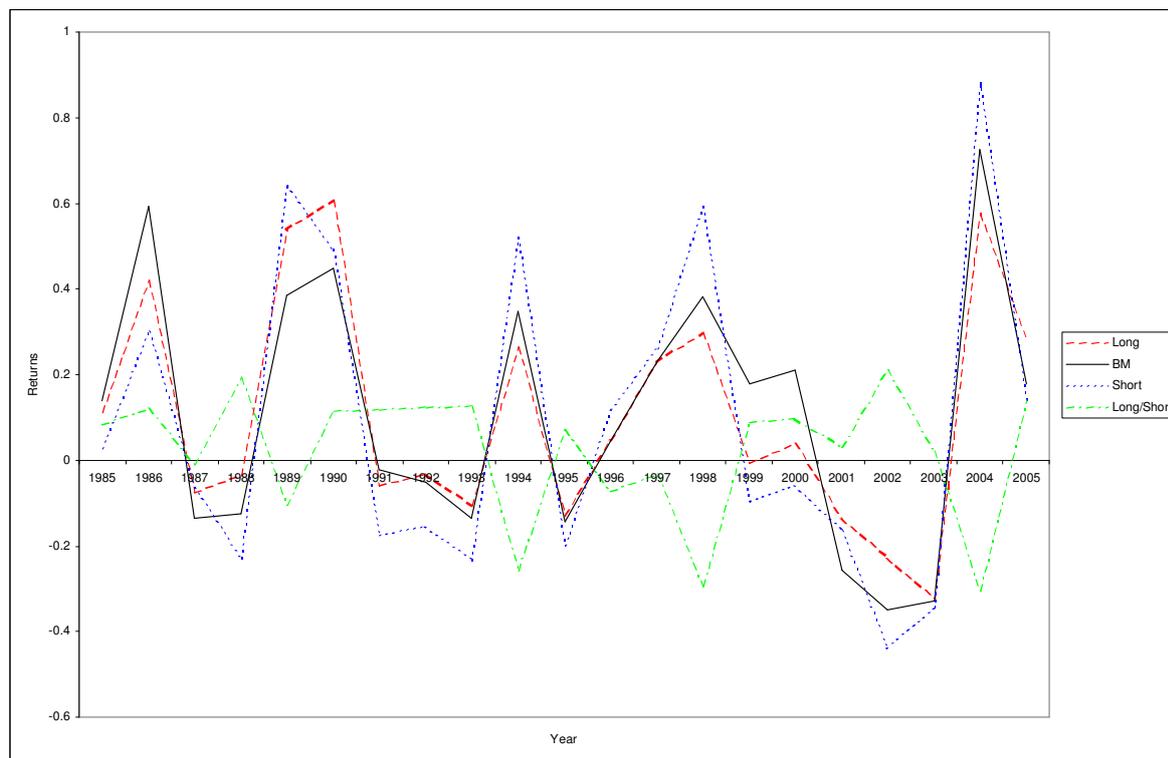
On the short side, an opposite approach is adopted, however positive absolute CFS values are allowed, as firms with long strings of negative CFS values are unlikely to exist for long periods of time as they face the possibility of bankruptcy. Thus, for the short side, stocks are required to have less than -20% average annual CFS growth for the past three years. If the string of absolute CFS values under consideration for a particular year contains a sign change or zero value, therefore making the -20% criteria impossible to observe, the corresponding stocks are kept on the short selection list. Next, the remaining stocks on both the short and long selection lists are held for a year after which an equally weighted average of their returns are calculated and compared to the BM. The plot of the Long, Short and Long/Short portfolios relative to the BM can be seen in Figure III-7.

As in the previous section, Table III-3 displays the mean returns, standard deviations and t-statistics of the portfolios. In this case, the results are not optimistic as all t-statistics are very small and far from being significant. The Long portfolio even underperforms the BM by 0.14%. All of this evidence hints that the first CAN SLIM™ screen is not effective in terms of providing the investor with positive returns.

Table III-3: t-statistics for Portfolio Returns after Annual CFS Growth Screen

	mean return (%)	standard deviation	t-statistic	p-value
Long - BM	-0.14	10.83	-0.06	0.9533
Short - BM	-2.35	15.58	-0.69	0.4974
Long/Short	2.21	15.10	0.67	0.5101

Table III-4 provides an annual breakdown of the number of stocks contained in the Long and Short portfolios after the Annual CFS Growth screen. It is evident that the number of remaining stocks drastically increases over time, partially due to the fact that many firms did not come to exist until later years and partially due to the fact that some data, especially CFS data, is not available for some constituents in the earlier years, despite being listed at that time on the CDAX®. Likewise, the number of stocks on the selection lists slightly tapers in recent years, which corresponds to a decrease in the overall availability of CFS data (Appendix 3).

Table III-4: Number of Stocks Remaining after Annual CFS Growth Screen where *t* = Portfolio Building Year

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Long	6	13	12	10	17	21	33	37	52	53	44	48	38	48	60	93	104	139	128	109	114
Short	3	3	5	5	9	6	5	10	14	23	34	35	46	54	57	48	80	160	226	254	263

Although quarterly CFS data, as specified by CAN SLIM™'s *"C"* (current earnings per share growth, which is substituted for in this anaylsis by CFS growth) factor, is not available, the next screen focuses on capturing the "accelerating" element of this factor by applying it to annual data. Only the stocks in the Long and Short portfolios that passed through the previous screen are subjected to this analysis. On the long side, the absolute CFS values must be increasing over the past three years. Hence, when choosing stocks on April 30th of year *t*, then the condition $CFS_{t-1} > CFS_{t-2} > CFS_{t-3} > CFS_{t-4}$ must be fulfilled. Additionally, the CFS growth in the most recent year must exceed the previous year's CFS growth by at least 50%.

Again, opposite screening requirements are employed on the short side so that the past three years must have decreasing absolute CFS figures (i.e., $CFS_{t-1} < CFS_{t-2} < CFS_{t-3} < CFS_{t-4}$) with the CFS growth in the most recent must have decreased by at least 50% from the previous year's CFS growth. As in the previous screen, all stocks having data with sign changes or zero values that prevent the evaluation criteria from being computed are allowed to pass through the screen.

Table III-5: Number of Stocks Remaining after Accelerating CFS Growth Screen where *t* = Portfolio Building Year

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Long	0	4	3	0	2	2	1	5	11	11	6	7	5	7	6	11	12	20	6	10	4
Short	0	0	0	0	1	0	0	0	2	2	4	2	2	5	4	2	4	5	17	14	18

The results of this screen are revealed in Table III-5, which shows the number of stocks remaining on each year's selection list after the accelerating CFS Growth screen. Thus, it is evident that this latest screen eliminates many of the stocks that are still present after the first screen. In fact, there are many years in the first half of the historical data range that do not have any stocks included in the portfolios, likely due to the data availability issues that were previously discussed. For this reason, the plot of the Long, Short and Long/Short portfolios relative to the BM shown in Figure III-8 includes only the returns from 1993 – 2005, years having stocks in both the Long and Short portfolios. By a quick visual inspection of this plot, it is easy to observe that the Long portfolios do not seem to regularly outperform the BM, nor do the Short portfolios seem to consistently underperform the BM.

Figure III-8: Returns of Stocks Remaining after Accelerating CFS Growth Screen
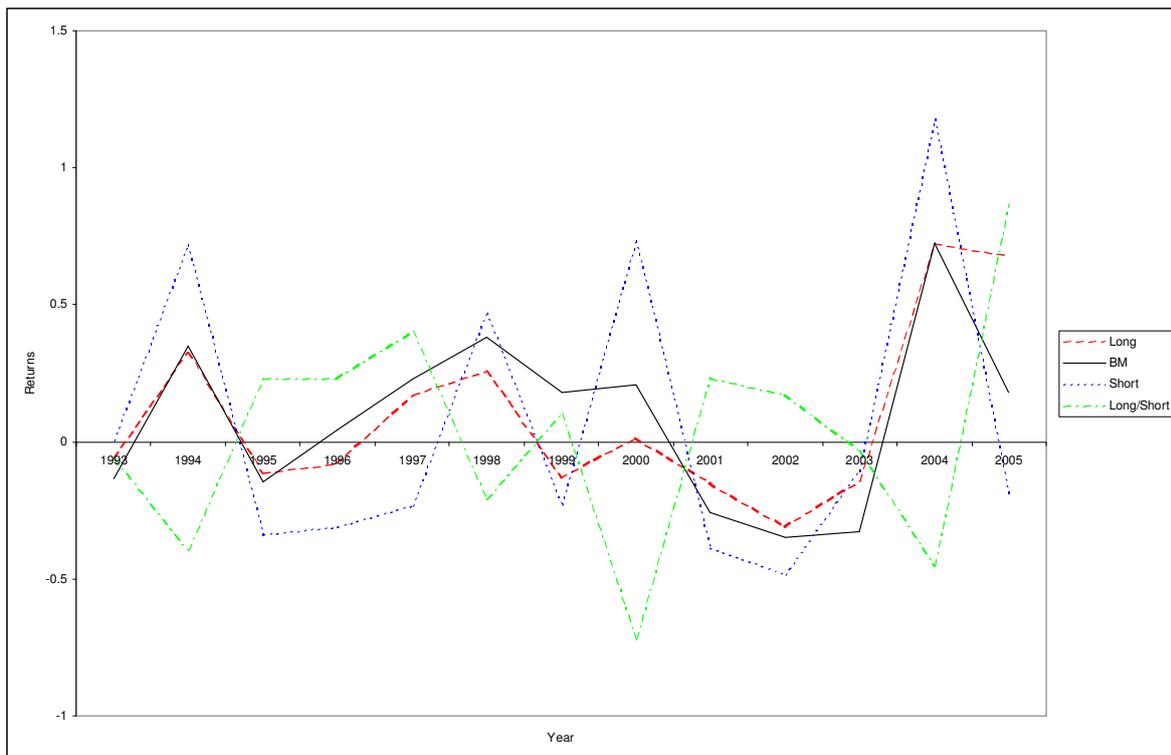
The results of the t-test analysis displayed in Table III-6 confirm what can be observed in Figure III-8; the performance of both the Long and Short portfolios is very poor. The t-statistics of all three portfolios when compared to the BM are extremely low, and once again, the Long underperforms the BM by an average of 1.91%. The values in Table III-6 are based on the returns from 1985 - 2005 of the Long and Short portfolios having at least one stock and the Long/Short portfolios that have at least one long and one short stock.

Table III-6: t-statistics for Portfolio Returns after Accelerating CFS Growth Screen

	mean return (%)	standard deviation	t-statistic	p-value
Long - BM	-1.91	16.97	-0.49	0.6296
Short - BM	-0.01	33.57	0.00	0.9991
Long/Short	0.09	40.73	0.01	0.9935

The final screen incorporates the *"L"* (leaders) factor which stipulates that one should select the best performing stocks based on their relative strengths, or price momentum. Therefore, this screen adds an additional restriction to the long and short selection lists remaining after the previous screen; stocks in the Long portfolio must be in the upper quartile of their annual momentum rankings while stocks in the Short portfolio must be in the bottom quartile.

Table III-7 exhibits the number of stocks in each portfolio after applying this third and final momentum screen to the stocks that passed through the previous two screens. Applying this latest screen further reduces the number of stocks in both the Long and Short portfolios due to the same previously discussed problems of data availability and firms not coming into existence until later years.

Table III-7: Number of Stocks Remaining after Momentum Screen where *t* = Portfolio Building Year

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Long	0	3	2	0	0	1	0	0	5	8	2	2	3	6	2	5	7	9	3	4	0
Short	0	0	0	0	1	0	0	0	2	1	0	2	1	5	1	1	3	5	5	5	7

The effectiveness of the momentum screen was evaluated following the same procedure as with the annual CFS growth and accelerating CFS growth screens.

The plot of the returns of the Long, Short and Long/Short portfolios in Figure III-9 fails to indicate an obvious trend of the portfolios' performances relative to that of the BM.

Figure III-9: Returns of Stocks Remaining after Momentum Screen
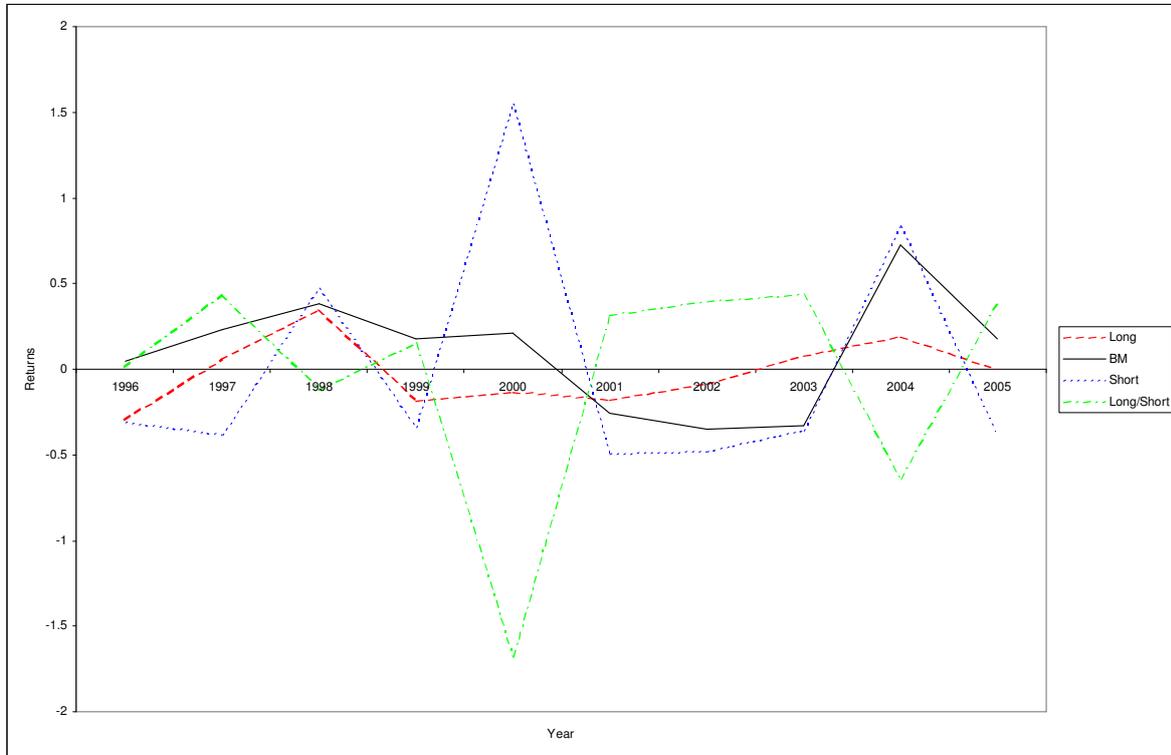
The accompanying t-test results found in Table III-8 include far from significant t-statistics of Long portfolios that underperform the BM by 2.88% on average and Short portfolios that overperform the BM by 0.96% on average. Additionally, the volatility for all portfolios is extremely high for all portfolios. Once again, the numbers in Table III-8 are based on the returns from 1985 - 2005 of the Long and Short portfolios compromised of at least one stock and the Long/Short portfolios that contain at least one long and one short stock. The stocks remaining in the Long and Short Portfolios for each year after the three-step preliminary screening can be seen in Appendix 4.

Table III-8: t-statistics for Portfolio Returns after Accelerating CFS Growth Screen

	mean return (%)	standard deviation	t-statistic	p-value
Long - BM	-2.88	29.29	-0.38	0.7091
Short - BM	0.96	53.67	0.06	0.9496
Long/Short	-10.60	64.73	-0.54	0.5989

The results of the CAN SLIM™ preliminary screening do not lead to an optimistic conclusion; by implementing this three-part stock screen, which integrates three of CAN SLIM™'s critical factors, there is no sign at this stage in the analysis that CAN SLIM™ will produce abnormal returns when implemented in the German market. However, CAN SLIM™ incorporates more than just the seven selection factors as O'Neil also stipulates exactly when to buy the stocks and suggests a strict adherence to a pre-defined stop loss rule. The next section applies these additional criteria to the stock selection lists.

1.2.4 CAN SLIM™ Full Screening

Despite the less than stellar outlook reached after the preliminary screening in the previous section, this section still aims to find abnormal returns with the addition of O'Neil's buy criterion and stop loss rule. O'Neil stipulates that as a part of CAN SLIM™'s *"N"* (new) factor, stocks should be purchased when they reach new 52-week price highs. He also strongly suggests introducing an 8% stop loss rule to the CAN SLIM™ portfolio as a risk management device.

In this part of the analysis, these additional two criteria are applied in an event study format to the selection list (as seen in Appendix 4) from last section's preliminary screening. That is, the event is defined as the day that the stocks reach a 52-week high within the year (April 30th of year *t* until April 29th of year *t+1*) that they are on the CAN SLIM™ preliminary screening selection list. Once the stocks are reach a price high, their returns are examined over the event window which is defined as the period from the day of the price high until the following April 30th at which time the same process begins for the CAN SLIM™ selection list of the following year. However, if at any time during the event window the stock loses more than 8% of its value, the stop loss rule is activated and the stock is immediately sold in order to prevent extreme losses. If no 52-week price high occurs during the year that the stock is on the selection list, then the stock is never purchased and is not included in the final CAN SLIM™ portfolios.

The following process describes the formation of the final CAN SLIM™ portfolios on the long side only. As in the preliminary screening, a "mirrored" CAN SLIM™

approach is applied to the short side. Here, an event study is performed which is instead triggered by a 52-week price low versus the 52-week price high as for the long side. Likewise, a stop loss rule of greater than an 8% rise in price is substituted for the equivalent 8% decline stop loss rule implemented on the long side. Appendix 5 lists the stocks remaining for each year in the Long and Short Portfolios after the completion of the CAN SLIM™ Full Screening process as well as the dates that their respective positions were opened and closed.

Figure III-10: Unadjusted Discrete Returns to Investor of Individual Stocks in Final CAN SLIM™ Long and Short Portfolios for all Years 1985 - 2005
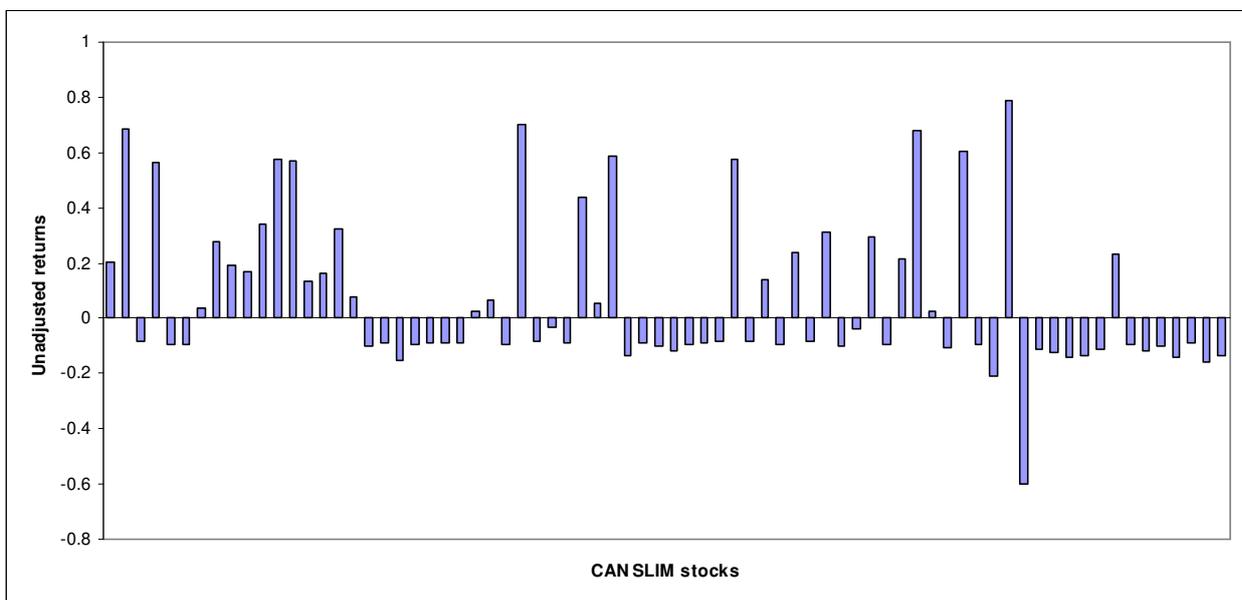
Next, the discrete returns for all of the stocks remaining in the CAN SLIM™ portfolios were calculated over their respective event windows. The returns to the investor of all stocks in both the Long and Short portfolios for all years are plotted in Figure III-10. From the statistics in Table III-9, it can be seen that the mean return of all individual stocks held for the specified dates listed in Appendix 5 in the CAN SLIM™ Long and Short portfolios across all years is 10.98% which is significant at 99%. The Short portfolios do result in a negative mean return of -1.67%, but this value is highly insignificant with a small t-statistic of -0.32.

Table III-9: t-statistics for Unadjusted Discrete Returns of Individual Stocks in Final CAN SLIM™ Long and Short Portfolios for all Years 1985 - 2005

	mean return (%)	standard deviation	t-statistic	p-value
Long	10.98	26.23	2.78	0.0081
Short	-1.67	28.92	-0.32	0.7541
Long/Short	7.21	27.55	2.25	0.0274

However, once the individual CAN SLIM™ stock returns are market-adjusted by subtracting a BM of the daily CDAX® returns across the same period for which each stock was held (as seen in Figure III-11 and Table III-10), it is revealed that the Long stocks underperform the BM by 2.06% while the Short stocks over perform the BM by 1.71%, with both the Long and Short portfolios having very small t-statistics.

Figure III-11: Market-adjusted Discrete Returns to Investor of Individual Stocks in Final CAN SLIM™ Long and Short Portfolios for all Years 1985 - 2005
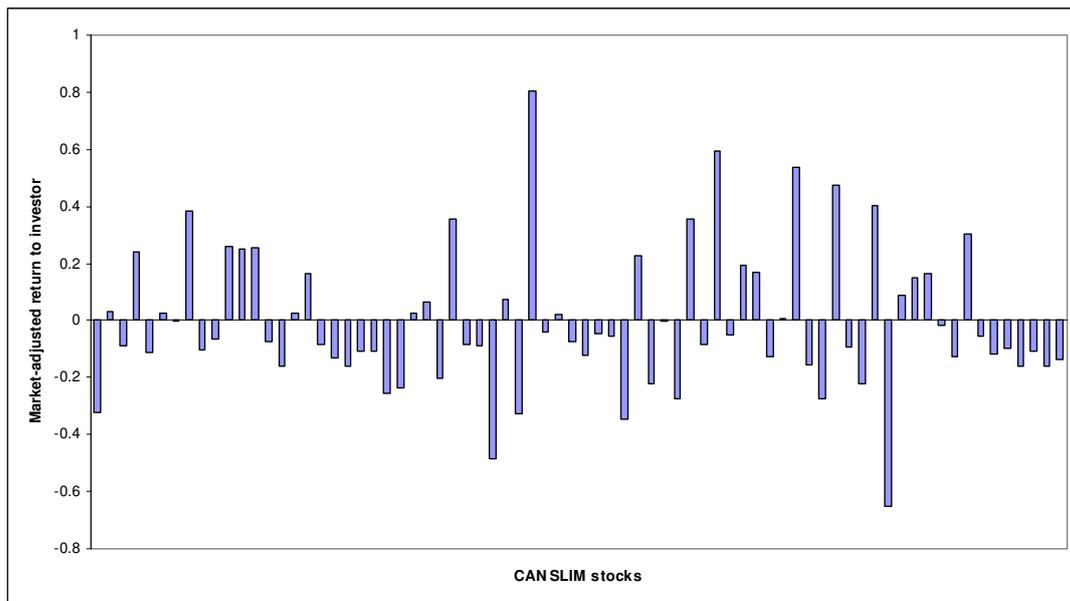
Obviously, these results do not support the notion that the CAN SLIM™ method of selecting stocks in the German market results in any positive abnormal returns. In terms of market efficiency in relation to CAN SLIM™, this analysis suggests that while the success of CAN SLIM™ in the U.S. may signal market inefficiency in the U.S., similar market inefficiencies do not seem to exist in the German market.

Table III-10: t-statistics for Market-adjusted Discrete Returns of Individual Stocks in Final CAN SLIM™ Long and Short Portfolios for all Years 1985 - 2005

	mean return (%)	standard deviation	t-statistic	p-value
Long - BM	-2.06	22.63	-0.60	0.5491
Short - BM	1.71	27.35	-0.34	0.7345
Long/Short	-0.53	24.54	-0.19	0.8531

Chapter IV
Conclusion

From the results of the full CAN SLIM™ screening procedure, the weak form of the EMH cannot be rejected. However, from the separate CFS growth and momentum analyses, it appears that individually, these factors may have some predictive power and appear to be promising selection criteria for long portfolios, which is consistent with the previous momentum studies in the German market as well as with CAN SLIM™ fundamentals. Furthermore, the feasibility of selecting stocks based on these criteria alone requires further evaluation of the profits after transaction costs.

The overall results are a bit startling, mainly in the respect that while CAN SLIM™ appears to yield consistently large abnormal profits in the U.S., the results for the German market are quite the opposite, despite all of the evidence of the correlation and common determinants of expected stock returns across both countries' equity markets. An interesting topic for further research would be to identify the different German and American market characteristics that reveal why CAN SLIM™ performs very differently in each market.

It is also possible that the limited size of the CDAX® investment universe, which does not include micro-cap stocks, compared to the universe of several thousand U.S. stocks used in other CAN SLIM™ analyses, severely limited the potential of the German CAN SLIM™ analysis, especially when CAN SLIM™ targets firms with small market capitalization. Also significantly reducing the size of the German investment universe was the lack of available data, particularly in the earlier years, which resulted in stocks with missing data being eliminated from CAN SLIM™ contention. Data quality issues might also be an issue, as seen in the distributions of the EPS and CFS data. This observable phenomenon is potentially due to the relaxed HGB reporting standards resulting from managers' attempts to smooth volatile figures or perhaps due to inaccurate data collecting techniques. While crosschecking techniques verified the accuracy of a sample of data, there is no way of determining to what extent the figures were smoothed.

Alternatively, perhaps the difference in CAN SLIM™'s performance can be attributed to the fact that a only scaled down version of CAN SLIM™ containing the quantitative but not qualitative factors was applied in the paper. Notably, certain subjective or impossible-to-program elements of the *"N"* (new) factor were omitted including new management, new products and new services. Also, the intra-industry analysis included in the *"L"* (leader or laggard) factor was also not performed here and the *"I"* (institutional sponsorship) factor was not at all considered. Perhaps, if a complete CAN SLIM™ analysis including all hard and soft elements were carried out, the results in the German market would be more similar to those in the U.S. market. However, implementing the non-programmable soft factors would require much

manual labor on a daily basis, thus making CAN SLIM™ impractical for an organization such as BGB to employ.

Appendix

Appendix 1: CDAX Constituents on May 18, 2005

3U TELEKOMMUNIKATION	ARBOMEDIA NET	BOSS (HUGO) PREF.
4MBO INTL.ELT.	ARMSTRONG DLW	BOV
A I S	ARNDT	BRAIN FORCE FINL.SLTN.
A S CREATION TAPETEN	ARTICON INTERGRALIS	BRAU UND BRUNNEN
AAP IMPLANTATE	ARTNET	BRAUEREI MONINGER
AAREAL BANK	ARTSTOR	BREMER VULKAN
ABACHO	ARXES NET.COMMS.CONS.	BRILLIANT
ABIT	ATOSS SOFTWARE	BROADNET MEDIA COMM.
ABWL.ROESCH MEDIZIN	AUDI	BRUEDER MANNESMANN
AC-SERVICE	AUGUSTA TECHS.	BUCH DE INTERNET
ACTION PRESS HLDG.	AUTANIA	BURGBAD PREF.
ACTRIS	AVA	CAATOOSEE
ADCAPITAL	AWD HOLDING	CAMELOT
ADIDAS-SALOMON	AXA KONZERN	CANCOM IT SYSTEME
ADLER REAL ESTATE	AXA KONZERN PREF.	CAPITALSTAGE
ADLINK INET.MEDIA	AZEGO	CARGOLIFTER
ADORI	B & L IMMOBILIEN	CARL ZEISS MEDITEC
ADS SYSTEM	B A U M	BIEN-ZENKER
ADVA OPTC.NETWORK	B I S BOERSEN INFO.	BIJOU BRIGITTE
ADV.PHOTONICS TECHS.	BAADER WERTPAH.	BILFINGER BERGER
ADVANCED MEDIEN	BABCOCK BORSIG	BILTRAIN
AGIPLAN TECHNOSOFT	BABCOCK BSH	BINTEC COMMUNICATIONS
AGIV REAL ESTATE	BALDA	BIODATA INFO.TECH.
AGOR	BANKGESELLSCHAFT BERLIN	BIOLITEC
AHAG WERTPAPIERHANDEL	BASF	BIOTEST
AHLERS	BASLER	BIOTEST PREF.
AHLERS PREF.	BAUVEREIN HAMBURG	BIRKERT & FLECKENSTEIN
AIG INTL.REAL ESTATE	BAYER	BKN INTERNATIONAL
AIXTRON	BAYER.HYPO-UND-VBK.	BMP
ALBIS LEASING	BAYWA REGD.	BMW
ALLBECON	BAYWA VINK	BMW PREF.
ALLGEIER HOLDING	BBS KRAFTFAHRZEUG PREF.	BOEWE SYSTEC
ALLGEM.ANLAGE VERWALTUNG	BEATE UHSE	BORUSSIA DORTMUND
ALLIANZ	BECHTLE	BOSS (HUGO)
ALNO	BEIERSDORF	CASH LIFE
ALPHAFORM	BERENTZEN-GRUPPE PREF.	CASH MEDIEN
ALTANA	BERLINER-HAN.HYPBK.	CBB HOLDING
AMADEUS FIRE	BERLINER EFFEKTEN	CCR LOGISTICS
AMATECH	BERTRANDT	CDV SOFTWARE ENTM.
AMB GENERALI HDG.	BERU	CE CONSUMER ELECTRO
ANALYTIK JENA	BETA SYSTEMS SOFTWARE	CEAG
ANDREAE-NORIS ZAHN	BHS TABLETOP	CELANESE
ANTWERPES	BHW HOLDING	CELESIO

CENIT SYSTEMHAUS	DEUTSCHER EISENHANDEL	ESSANELLE HAIR GROUP
CENTROTEC	DEUTSCHE EUROSHOP	EUROHYPO
CEOTRONICS	DT.HYPBK.HANN.BL.	EUROMED
CEWE COLOR HDG.	DT.IMMOBILIEN HOLDING	EUROMICRON
CEYONIQ	DEUTSCHE LUFTHANSA	EVOTEC OAI
CINE-MEDIA FILM	DEUTSCHE POST	F A M E F&M ENTM.
CINEMAXX	DEUTSCHE POSTBANK	FARMATIC BIOTECH
CNV VERMOEGENSVERWALTUNG	DEUTSCHE REAL ESTATE	FELTEN & GUILL. ENERGIE
CO DON	DEUTSCHE STEINZEUG	FIELMANN
COMDIRECT BANK	DEUTSCHE TELEKOM	FJH
COMMERZBANK	DEUTZ	FLUXX
COMPUTEC MEDIA	DIDIER-WERKE	FORIS
COMPUTERLINKS	DIERIG HOLDING	FORTEC ELEKTRONIK
COMTRADE	DIS DT.INDUSTRIE SVS.	FRAPORT
CONCORD EFFEKTEN	DKM WERTPAH.	FREENET
CONDOMI	DR.SCHELLER COSMETICS	FRESENIUS
CONERGY	DOUGLAS HOLDING	FRESENIUS MED.CARE
CONSTANTIN FILM	DRAEGERWERK PREF.	FRESENIUS MED.CARE PREF.
CONTIGAS	DRILLISCH	FRESENIUS PREF.
CONTINENTAL	DUERKOPP ADLER	FRIATEC
COR INSURANCE TECH.	DUERR	FRITZ NOLS GBL.EQ.SVS.
CORDIER (ROBERT)	DVB BANK	FROEHLICH BAU
CPU SOFTWAREHOUSE	DYCKERHOFF	FROEHLICH BAU PREF.
CREATON PREF.	DYCKERHOFF PREF.	FUCHS PETROLUB
CTS EVENTIM	E ON	FUCHS PETROLUB PREF.
CURANUM	E-M-S NEW MEDIA	FUNKWERK
CURASAN	EASY SOFTWARE	GAP
CURTIS 1000 EUROPE	ECKERT & ZIEGLER	GARANT SCHUH+MODE PREF.
CUSTODIA HOLDINGS	EDEL MUSIC	GCI MANAGEMENT
CYBIO	EHLEBRACHT	GEDYS INET.PRODUCTS
CYCOS	EHLEBRACHT PREF.	GELSENWASSER
D LOGISTICS	EICHBORN VERLAG	GENESCAN EUROPE
D+S ONLINE	EINHELL HANS PREF.	GERATHERM MEDICAL
DAB BANK	EISEN & HUETTENWERK	GERMAN BROKERS
DAIMLERCHRYSLER	ELEPHANT SEVEN	GESCO
DATA MODUL	ELEXIS	GFK
DATADESIGN	ELMOS SEMICONDUCTOR	GFN PREF
DATASAVE	ELRINGKLINGER	GFT TECHNOLOGIES
DBV-WINTERTHUR HOLDING	ELSA	GILDEMEISTER
DCI DATABASE	EM TV AG	GIRINDUS
DEAG DEUTSCHE ENTM.	EMPRISE MANAGEMENT	GLOBALWARE
DEBITEL	ENERGIE BADEN WUERT.	GLUNZ
DEGUSSA	ENERGIEKONTOR	GLUNZ PREF.
DEUTSCHE BALATON	EPCOS	GOLD-ZACK
DEUTSCHE BANK	EPIGENOMICS	GONTARD & METALLBANK
DEUTSCHE BET.	ERGO VERSICHERUNG	GPC BIOTECH
DEUTSCHE BOERSE	ESCADA	GRAMMER
DT.EFF.&WECHSEL	ESCOM	GRAPHITWERK KROPFMUEHL

GREENWICH BETEILIGUNGEN	INIT	LEICA CAMERA
GRENKELEASING	INTERNOLIX	LEIFHEIT
GROUP TECHNOLOGIES	INTERSEROH	LEONI
H & R WASAG	INTERSHOP COMMS.	LINDE
H5B5 MEDIA	INTERTAINMENT	LINDNER HDG.
HAITEC	INTICOM SYSTEMS	LINOS
HAMBORNER	IPC ARCHTEC	LINTEC INFO.TECH.
HANNOVER RUCK.	ISION INTERNET	LION BIOSCIENCE
HARPEN	ISRA VISION SYSTEM	LIPRO AG LOGISTIK
HAWESKO HLDG.	ITELLIGENCE	LOBSTER NET.STORAGE
HEIDELBERGCEMENT	IVG IMMOBILIEN	LOEWE
HEIDELB.DRUCKMASCHINE	IVU TRAFFIC TECHS.	LPKF LASER & ELTN.
HEILER SOFTWARE	IWKA	LS TELCOM
HEINKEL	IXOS SOFTWARE	LUDWIG BECK
HELIAD EQUITY PARTNERS	JACK WHITE PRD.	M & S ELEKTRONIK
HELKON MEDIA	JENOPTIK	M-TECH TECHNOLOGIE PREF.
HENKEL	JETTER	MAIER & PARTNER
HENKEL PREF.	JUNGHEINRICHPREF.	MAINOVA
HERLITZ	K&M MOEBEL	MAN
HERMLE BERTHOLD PREF.	K + S	MAN PREF.
HERZOG TELECOM	KABEL NEW MEDIA	MANAGEMENT DATA
HEYDE	KAESSBOHRER GELAENDE	MANIA TECHNOLOGIES
HIT INTL.TRADING	KAMPA-HAUS	MANNHEIMER AG HOLDING
HOCHTIEF	KAP-BETEILIGUNGS	MARBERT
HOECHST	KARSTADT QUELLE	MARSEILLE-KLINIKEN
HOEFT & WESSEL	KAUFHALLE	MASTERFLEX
HOENLE(DR.)	KAUFRING	MATERNUS-KLINIKEN
HOLSTEN-BRAUEREI	KENVELO	MAUSER WALDECK
HOLZMANN PHILIPP	KINOWELT MEDIEN	MAX HOLDING
HORNBACH-BAUMARKT	KLASSIK RADIO	MAXDATA
HORNBACH HOLDING PREF.	KLEINDIENST DATEN	MB SOFTWARE
HORNSCHUCH KONRAD	KLING JELKO DEHMEL	MCS SYSTEME
HSBC TRINKAUS & BURKHD.	KLOECKNER-WERKE	MEDIA
HUCKE	KNORR CAPITAL PARTNER	MEDIA (NETCOM)
HYMER	KOEGEL PREF.	MEDIANTIS
HYPO REAL ESTATE HLDG.	KOEHLER & KRENZER FASH.	MEDICLIN
I FAO	KOELN.RUCK.	MEDIGENE
I-D MEDIA	KOELN.RUCK.GESELL. REGD.	MEDION
IBS	KOENIG & BAUER	MEDISANA
IDS SCHEER	KOLBENSCHMIDT PIERBURG	MENSCH & MASCHIN.SFTW.
IFA HOTEL & TOURISTIK	KONTRON	MERCK KGAA
IKB DT.INDSTRBK.	KRONES	MET(@)BOX
IM INTL.MEDIA	KSB	METRO
IMW IMMOBILIEN	KSB PREF.	METRO PREF.
IN-MOTION	KUEHNLE KOPP&KAUSCHPREF	MG TECHNOLOGIES
INDUS HOLDING	KUEHNLE KOPP & KAUSCH	MICROLOG LOGISTICS
INFINEON TECHNOLOGIES	KULMBACHER BRAUEREI	MICROLOGICA
INFOMATEC INTGRTD.INFO.SYS.	LANXESS	MIFA MITTELDEUTSCHE FAHRRAD-WERKE
INFOR BUSINESS SLTN.	LECHWERKE	MINERALBR.UEB.

MINERALBR.UEB.PREF.	PFEIFFER VACUUM TECH.	RSE GRUNDBESITZ UND BET.
MIS	PFLEIDERER	RTV FAMILY ENTM.
MLP	PGAM ADVD.TECHS.	RUECKER
MME ME MYSELF&EYE	PHENOMEDIA	RWE
MOBILCOM	PHOENIX	RWE PREF.
MOEBEL WALTHER	PILKINGTON DEUTSCHLAND	SACHSENMILCH
MOEBEL WALTHER PREF.	PIPER	SACHSENRING AUTO
MOENUS	PIRONET NDH	ST.-GOBAIN OBERLAND GLAS
MOKSEL A	PITTLER MASCHINEN	SALTUS TECHNOLOGY
MOLOGEN	PIXELPARK	SALZGITTER
MORPHOSYS	PLAMBECK NEUE ENGE.	SANACORP PHARAMAHANDEL PREF.
MOSAIC SOFTWARE	PLASMASELECT	SANDER JIL PREF.
MPC MUENCHMEYER CAP.	PLENUM	SAP
MUEHL PRODUCT & SER.	PONAXIS	SAP SYS.INTEGRATION
MUEHLBAUER HOLDING	PONGS & ZAHN	SARTORIUS
MUELLER-LILA LOGISTICS	POPNET INTERNET	SARTORIUS PREF.
MUNCH.RUCK.REGD.	PORSCHE PREF.	SCA HYGIENE PRODUCTS
MVV ENERGIE	PORTA SYSTEMS	SCHALTBAU HOLDING
MWB WERTPAPIERHANDELS	PREMIERE	SCHERING
MWG-BIOTECH	PRIMACOM	SCHLOTT GRUPPE
NEMETSCHEK	PRO DV SOFTWARE	SCHNEIDER TECHS.
NESCHEN	PROCON MULTIMEDIA	SNP SHNDR-NEUREITHER
NET IPO	PRODACTA	SCHOEN & CIE
NET@	PROGRESS-WERK	SCHOLZ & FRIENDS
NETLIFE	PROSIEBEN SAT 1 PF.	SCHULER PREF.
NEUE SENTIMENTAL FILM	PROUT	SCHUMAG
NEXUS	PSB	SCHWAELBCHEN MOLKEREI
NORCOM INFO.TECH.	PSI	SCHWARZ PHARMA
NORDDEUTSCHE AFFINERIE	PULSION MEDICAL SYS.	SCHWEIZER ELT.
NORDEX	PUMA	SECUNET SCTY.NETWORKS
NOVASOFT	PVA TEPLA	SEKTKELLEREI SCHLOSS WACHENHEIM
NOVEMBER	QSC	SENATOR ENTM.
NUERNBERGER BET.REGD.	QUANTE PREF.	SER SYSTEME
OAR CONSULTING	R STAHL	SERO ENTSORGUNG
ODEON FILM	RATIONAL	SGL CARBON
OHB TECHNOLOGY	REAL	SHS INFORMATIONS
ONVISTA	REALTECH	SIBRA BETEILIGUNGS
ORBIS	REFUGIUM HOLDING	SIEMENS
P & I PERSONAL & INFO	REPOWER SYSTEMS	SILICON SENSOR
P&T TECHNOLOGY	RHEINER MODEN	SIMONA
P-D INTERGLAS TECHS	RHEINMETALL	SINGULUS TECHNOLOGIES
PA POWER AUTOMATION	RHEINMETALL PREF.	SINNER
PAION	RHOEN-KLINIKUM	SINNERSCHRADER
PANDATEL	RHOEN-KLINIKUM PREF.	SIXT
PARAGON	RICARDO	SIXT PREF.
PARK & BELLHEIMER	RINOL	SM WIRTSCHAFTSBERATUNG
PARSYTEC	ROEDER ZELT.UND SERVICE	SOFTING
PC-SPEZIALIST	ROHWEDDER	SOFTLINE
PC-WARE INFO TECHS.	ROSENTHAL	SOFTM SFTW.BERATUNG

SOFTMATIC	TRIPLAN	WEBER (GERRY) INTL.
SOFTSHIP	TRIUMPH INTL.	WEDECO WATER TECHNOLOGY
SOFTWARE	TRIUS	WELLA
SOLAR FABRIK	TTL INFORMATION	WELLA PREF.
SOLARWORLD	TUI	WERU
SOLON FUER SOLARTECHNIK	TURBON	WESTAG & GETALIT
SPARTA AG	TV-LOONLAND	WESTAG & GETALIT PREF.
SPLENDID MEDIEN	UBAG UNTERNEHMER BET.	WIGE MEDIA
SPORTWETTEN	UMS UTD.MEDICAL SYS.	WINCOR NIXDORF
SPRINGER (AXEL)	UMWELTKONTOR	WINKLER + DUENNEBIER
SPUETZ	UNIPROF REAL ESTATE	WINTER
STADA ARZNEIMITTEL	UNITED INTERNET	WIRE CARD
STEAG HAMATECH	UNITED LABELS	WMF
STO PREF.	USU SOFTWARE	WMF PREF.
STODIEK EUROPA IMMOB.	UTIMACO SAFEWARE	WUENSCHE
STOEHR	UZIN UTZ	WUESTENROT & WUERTT.
STOLBERGER TELECOM	VALUE MANAGEMENT	YMOS
STRABAG	VARETIS	ZAPF CREATION
STRATEC BIOMEDICAL SYS.	VARTA	
STUTT.HOFBRAEU	VATTENFALL EUROPE	
SUEDZUCKER	VBH HOLDING	
SUESS MICROTECH	VCB BEST OF VC	
SUNBURST MRCHNDSG.	VCL FILM + MEDIEN	
SUNWAYS	VDN VER.DTL.NICKELWERKE	
SURTECO	VECTRON SYSTEMS	
SWING ENTM.MEDIA	VGT INDUSTRIE	
SYSKOPLAN	VILLEROY & BOCH PREF.	
SYZYGY	VIVA MEDIA	
SZ TESTSYSTEME	VIVACON	
T-ONLINE	VIVANCO GRUPPE	
TA TRIUMPH-ADLER	VK MUEHLEN	
TAG TEGERNSEEBAHN IM.	VOGT ELECTRONIC	
TAKKT	VOGT ELECTRONIC PREF.	
TARKETT	VOLKSWAGEN	
TC UNTERHALTUNGS	VOLKSWAGEN PREF.	
TDS INFORMATIONS TECH.	VOSSLOH	
TEAMWORK INFORMATION	W E T AUTOMOTIVE	
TECHEM	W O M WORLD OF MDCIN.	
TECHNOTRANS AG	WALTER	
TELEGATE	WALTER BAU	
TELES	WALTER BAU PREF.	
TFG CAPITAL	WANDERER-WERKE	
THYSSENKRUPP	WAPME SYSTEMS	
TIAG TABBERT-INDUSTRIE	WASGAU PRD.& HANDEL	
TIPTEL	WASHTEC	
TISCON	WAVELIGHT LASER TECHS.	
TOMORROW FOCUS	WCM BETEILIGUNG	
TRAVEL24.COM	WEB DE	
TRIA IT-SOLUTIONS	WEBAC-HOLDING	

Appendix 2: Regression Tables: EViews Output

a.   Model (III.1) - CFS growth on market-adjusted returns

Dependent Variable: AF
Method: Least Squares
Date: 06/27/05   Time: 16:33
Sample(adjusted): 1 4904
Included observations: 4904 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.096858	0.007451	-12.99976	0.0000
AE	-0.012322	0.011158	-1.104346	0.2695
R-squared	0.000249	Mean dependent var		-0.096997
Adjusted R-squared	0.000045	S.D. dependent var		0.521701
S.E. of regression	0.521689	Akaike info criterion		1.536918
Sum squared resid	1334.126	Schwarz criterion		1.539568
Log likelihood	-3766.523	F-statistic		1.219580
Durbin-Watson stat	0.001574	Prob(F-statistic)		0.269497

b.   Model (III.1) - Normalized CFS growth on market-adjusted returns trimmed to +/-3 standard deviations

Dependent Variable: AH
Method: Least Squares
Date: 06/27/05   Time: 17:29
Sample(adjusted): 1 4828
Included observations: 4828 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.035521	0.009396	3.780578	0.0002
AG	0.024209	0.028858	0.838921	0.4016
R-squared	0.000146	Mean dependent var		0.035575
Adjusted R-squared	-0.000061	S.D. dependent var		0.652813
S.E. of regression	0.652833	Akaike info criterion		1.985423
Sum squared resid	2056.797	Schwarz criterion		1.988108
Log likelihood	-4790.812	F-statistic		0.703789
Durbin-Watson stat	0.000350	Prob(F-statistic)		0.401555

c.   Model (III.2) - Price Momentum

Dependent Variable: J
Method: Least Squares
Date: 06/22/05   Time: 19:10
Sample(adjusted): 1 6360
Included observations: 6360 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.104290	0.007254	-14.37672	0.0000
K	0.176175	0.011735	15.01300	0.0000
R-squared	0.034236	Mean dependent var		-0.130484
Adjusted R-squared	0.034084	S.D. dependent var		0.571348
S.E. of regression	0.561526	Akaike info criterion		1.683998
Sum squared resid	2004.752	Schwarz criterion		1.686123
Log likelihood	-5353.113	F-statistic		225.3901
Durbin-Watson stat	1.837711	Prob(F-statistic)		0.000000

d.   Model (III.2) - Price Momentum - trimmed to +/-3 standard   deviations
Dependent Variable: M
Method: Least Squares
Date: 06/29/05   Time: 13:10
Sample(adjusted): 1 6115
Included observations: 6115 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.063110	0.009686	6.515625	0.0000
N	0.159883	0.012646	12.64279	0.0000
R-squared	0.025481	Mean dependent var		0.076482
Adjusted R-squared	0.025322	S.D. dependent var		0.762608
S.E. of regression	0.752891	Akaike info criterion		2.270534
Sum squared resid	3465.120	Schwarz criterion		2.272731
Log likelihood	-6940.157	F-statistic		159.8401
Durbin-Watson stat	1.825137	Prob(F-statistic)		0.000000

e.   Model (III.3): CAPM - Price Momentum - Top 10% Portfolio
Dependent Variable: SER04
Method: Least Squares
Date: 07/18/05   Time: 16:25
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.138254	0.068913	2.006204	0.0567
SER02	1.048533	0.199011	5.268732	0.0000
R-squared	0.404097	Mean dependent var		0.167025
Adjusted R-squared	0.378189	S.D. dependent var		0.450319
S.E. of regression	0.355099	Akaike info criterion		0.843777
Sum squared resid	2.900190	Schwarz criterion		0.941288
Log likelihood	-8.547219	F-statistic		15.59692
Durbin-Watson stat	2.419152	Prob(F-statistic)		0.000638

f.   Model (III.4): Market Model - Price Momentum - Top 10% Portfolio
Dependent Variable: SER03
Method: Least Squares
Date: 07/18/05   Time: 16:15
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.136032	0.068002	2.000413	0.0574
SER01	1.031675	0.179019	5.762949	0.0000
R-squared	0.406050	Mean dependent var		0.251764
Adjusted R-squared	0.380226	S.D. dependent var		0.451241
S.E. of regression	0.355242	Akaike info criterion		0.844585
Sum squared resid	2.902533	Schwarz criterion		0.942095
Log likelihood	-8.557313	F-statistic		15.72382
Durbin-Watson stat	2.412368	Prob(F-statistic)		0.000613

g.   Model (III.3): CAPM - Price Momentum - Bottom 10% Portfolio
Dependent Variable: SER06
Method: Least Squares
Date: 07/18/05   Time: 16:32
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.032654	0.031748	-1.028548	0.3144
SER02	1.176629	0.138489	8.496200	0.0000
R-squared	0.792156	Mean dependent var		-0.000368
Adjusted R-squared	0.783120	S.D. dependent var		0.360923
S.E. of regression	0.168083	Akaike info criterion		-0.652094
Sum squared resid	0.649797	Schwarz criterion		-0.554583
Log likelihood	10.15117	F-statistic		87.66012
Durbin-Watson stat	1.768798	Prob(F-statistic)		0.000000

h.   Model (III.4): Market Model - Price Momentum - Bottom 10% Portfolio
Dependent Variable: SER05
Method: Least Squares
Date: 07/18/05   Time: 16:41
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.047022	0.029132	-1.614134	0.1201
SER01	1.171290	0.130475	8.977094	0.0000
R-squared	0.797138	Mean dependent var		0.084371
Adjusted R-squared	0.788318	S.D. dependent var		0.365639
S.E. of regression	0.168227	Akaike info criterion		-0.650390
Sum squared resid	0.650906	Schwarz criterion		-0.552879
Log likelihood	10.12987	F-statistic		90.37747
Durbin-Watson stat	1.763153	Prob(F-statistic)		0.000000

i.   Model (III.3): CAPM - Price Momentum - Long/Short Portfolio
Dependent Variable: SER08
Method: Least Squares
Date: 07/18/05   Time: 16:52
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.086549	0.096933	0.892875	0.3812
SER02	-0.141941	0.310778	-0.456727	0.6522
R-squared	0.006212	Mean dependent var		0.082654
Adjusted R-squared	-0.036996	S.D. dependent var		0.491667
S.E. of regression	0.500679	Akaike info criterion		1.530915
Sum squared resid	5.765624	Schwarz criterion		1.628425
Log likelihood	-17.13643	F-statistic		0.143770
Durbin-Watson stat	2.198516	Prob(F-statistic)		0.708039

j.   Model (III.4): Market Model - Price Momentum - Long/Short Portfolio
Dependent Variable: SER07
Method: Least Squares
Date: 07/18/05   Time: 16:55
Sample(adjusted): 1 25
Included observations: 25 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.183054	0.093003	1.968260	0.0612
SER01	-0.139615	0.294109	-0.474705	0.6395

R-squared	0.006360	Mean dependent var	0.167393
Adjusted R-squared	-0.036841	S.D. dependent var	0.487914
S.E. of regression	0.496820	Akaike info criterion	1.515441
Sum squared resid	5.677093	Schwarz criterion	1.612951
Log likelihood	-16.94301	F-statistic	0.147227
Durbin-Watson stat	2.208771	Prob(F-statistic)	0.704724

k.   Model (III.5): Hedge Fund Regressions - Composite
Dependent Variable: LS_MOMPORT
Method: Least Squares
Date: 08/16/05   Time: 10:45
Sample: 1 11
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.265098	0.228812	1.158588	0.2764
COMPOSITE	-1.123567	1.455597	-0.771894	0.4600

R-squared	0.062092	Mean dependent var	0.207909
Adjusted R-squared	-0.042120	S.D. dependent var	0.703338
S.E. of regression	0.717998	Akaike info criterion	2.338265
Sum squared resid	4.639688	Schwarz criterion	2.410610
Log likelihood	-10.86046	F-statistic	0.595821
Durbin-Watson stat	1.960425	Prob(F-statistic)	0.459964

l.   Model (III.5): Hedge Fund Regressions - Neutral
Dependent Variable: LS_MOMPORT
Method: Least Squares
Date: 08/16/05   Time: 10:46
Sample: 1 11
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.190610	0.233192	0.817397	0.4348
NETURAL	0.448111	1.786621	0.250815	0.8076

R-squared	0.006941	Mean dependent var	0.207909
Adjusted R-squared	-0.103399	S.D. dependent var	0.703338
S.E. of regression	0.738806	Akaike info criterion	2.395403
Sum squared resid	4.912509	Schwarz criterion	2.467748
Log likelihood	-11.17472	F-statistic	0.062908
Durbin-Watson stat	2.396367	Prob(F-statistic)	0.807590

I.   Model (III.5): Hedge Fund Regressions – Long/Short
Dependent Variable: LS_MOMPORT
Method: Least Squares
Date: 08/16/05   Time: 10:44
Sample: 1 11
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.200177	0.235022	0.851741	0.4164
LSE	0.132698	1.252852	0.105917	0.9180
R-squared	0.001245	Mean dependent var		0.207909
Adjusted R-squared	-0.109728	S.D. dependent var		0.703338
S.E. of regression	0.740922	Akaike info criterion		2.401123
Sum squared resid	4.940688	Schwarz criterion		2.473467
Log likelihood	-11.20617	F-statistic		0.011218
Durbin-Watson stat	2.358096	Prob(F-statistic)		0.917971

Appendix 3: Number of Available Data per Year for the 683 CDAX® Constituents

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Price	84	85	85	86	89	95	100	111	120	187	208	227	239
CFS	60	58	64	84	98	101	103	134	174	186	199	209	221

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Price	245	251	265	277	297	328	424	566	654	666	671	672	683
CFS	249	262	272	353	475	563	587	649	632	607	588	395	na

Appendix 4: Long and Short Portfolios after CAN SLIM™ Preliminary Screening

	1984	1985	1986
Long	na	SCA HYGIENE PRODUCTS SCHERING AG SIEMENS AG	E.ON AG VOLKSWAGEN
Short	na	na	na

	1987	1988	1989
Long	na	na	CELESIO AG
Short	na	DEUTZ AG	na

	1990	1991	1992
Long	na	na	AVA ALLG. HANDELS. CELESIO AG HORNBACH HOLDING AG IMW IMMOBILIEN AG WERU AG
Short	na	na	SCHNEIDER TECHNOLOG SCHOEN & CIE AG

	1993	1994	1995
Long	COMMERZBANK AG EHLEBRACHT AG HORNBACH HOLDING AG RHOEN-KLINIKUM AG RHOEN-KLINIKUM AG PREF RWE AG SIBRA BETEILIGUNG VBH HOLDING AG	RHOEN-KLINIKUM AG RHOEN-KLINIKUM AG PREF	HORNBACH HOLDING AG VBH HOLDING AG
Short	WALTER AG	na	CEAG AG SCHLOSS WACHENHEIM

	1996	1997	1998
Long	RHOEN-KLINIKUM AG RHOEN-KLINIKUM AG PREF TAG TEGERNSEE	BMW BMW PREF FRESENIUS AG FRESENIUS AG PREF HEIDELBERGCEMENT AG MLP AG	RHEIN AG PREF: VOSSLOH AG
Short	BHS TABLETOP	ADLER REAL ESTATE AG BABCOCK BORSIG AG BHS TABLETOP PHILIPP HOLZMANN AG VK MUEHLEN AG	KENVELO AG

	1999	2000	2001
Long	BBS FAHRZEUGTECHNIK HSBC TRINKAUS & BURK HYMER AG SIXT SIXT PREF	BHW HOLDING AG CINEMEDIA FILM AG CONCORD EFFEKTEN AG MLP AG RSE GRUNDBESITZ AG SAP AG ZAPF CREATION AG	ALTANA AG HUGO BOSS AG HUGO BOSS AG PREF ESCADA AG FIELMANN AG PROCON MULTI MEDIA SCHLOTT GRUPPE AG STADA ARZNEIMITTEL WEDECO AG WATER TECH
Short	M-TECH TECHNOLOGIE	BETA SYSTEMS COMPUTEC MEDIA AG KAUFRING AG	COMPUTEC MEDIA AG JACK WHITE PRODUCT KLEINDIENST DATENTEC PORTA SYSTEMS SOFTMATIC

	2002	2003	2004
Long	BILFINGER BERGER AG GARANT SCHUH & MODE PUMA AG RUDOLF D.S.	STADA ARZNEIMITTEL TARKETT-SOMMER AG WELLA AG WELLA AG	na
Short	GOLD-ZACK M+S ELEKTRONIK AG PORTA SYSTEMS WALTER BAU-AG WALTER BAU-AG PREF	ALLBECON AG BRILLIANT AG VIVANCO GRUPPE AG WORLD OF MEDICINE AG WCM BETEILIGUNG	DBV WINTERTHUR DUERKOPP ADLER MARBERT HOLDING AG PLAMBECK AG ROSENTHAL WCM BETEILIGUNG WINTER AG

Appendix 5: Long and Short Portfolios after CAN SLIM™ Full Screening

		1985	1989	1992	1993	1994
		SCHERING	CELESIO	CELESIO	RHOEN-KLINIKUM	RHOEN-KLINIKUM
	open	6/19/85	5/5/89	4/30/92	5/12/93	8/8/94
	close	4/29/86	4/29/90	6/4/92	4/29/94	4/29/95
	return	0.2008	0.5651	-0.0942	0.5742	0.0778
	CDAX	0.5243	0.3256	0.0161	0.3250	-0.0849
	return - CDAX	-0.3235	0.2394	-0.1103	0.2493	0.1627
		SCA HYGIENE		IMW IMMOBILIEN	RHOEN-KLINIKUM PREF.	RHOEN-KLINIKUM PREF.
	open	5/22/85		9/17/92	5/13/93	10/14/94
	close	4/29/86		4/29/93	4/29/94	12/5/94
	return	0.6860		0.0395	0.5709	-0.0999
	CDAX	0.6533		0.0429	0.3171	-0.0162
	return - CDAX	0.0327		-0.0034	0.2538	-0.0838
		SIEMENS		HORNBACH HLDG PREF	HORNBACH HLDG PREF	
	open	6/12/85		5/4/92	7/9/93	
	close	7/26/85		8/11/92	4/29/94	
	return	-0.0813		-0.0935	0.1702	
	CDAX	0.0050		-0.1195	0.2351	
	return - CDAX	-0.0864		-0.0649	-0.0649	
				WERU	COMMERZBANK	
	open			5/18/92	6/16/93	
	close			4/29/93	4/29/94	
	return			0.2783	0.1895	
Long	CDAX			-0.1040	0.2936	
	return - CDAX			0.3822	-0.1041	
					EHLEBRACHT	
	open				10/22/93	
	close				4/29/94	
	return				0.3397	
	CDAX				0.0779	
	return - CDAX				0.2618	
					RWE	
	open				7/20/93	
	close				4/29/94	
	return				0.1328	
	CDAX				0.2066	
	return - CDAX				-0.0738	
					SIBRA BETEILIGUNGS	
	open				5/3/93	
	close				4/29/94	
	return				0.1623	
	CDAX				0.3229	
	return - CDAX				-0.1607	
					VBH HOLDING	
	open				6/16/93	
	close				4/29/94	
	return				0.3209	
	CDAX				0.2936	
	return - CDAX				0.0272	
				SCHOEN & CIE		
	open			5/5/92		
	close			11/5/92		
	return			0.0976		
	CDAX			-0.1779		
	return - CDAX			0.2755		
				SCHNEIDER TECHS.		
	open			10/14/92		
	close			4/29/93		
	return			-0.2371		
	CDAX			0.1196		
	return - CDAX			-0.3567		
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
Short	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					

		1995	1996	1997	1998	1999
Long		HORNBACH HLDG PREF	TAGTEGERNSEEBAHN	BMW	RHEINMETALL	BBS KRAFT PREF
	open	6/16/95	4/9/97	5/2/97	5/4/98	6/24/99
	close	8/10/95	4/17/97	8/15/97	8/28/98	2/10/00
	return	-0.0889	-0.1510	-0.0870	-0.0810	-0.0872
	CDAX	0.0425	0.0079	0.1681	0.0032	0.3994
	return - CDAX	-0.1314	-0.1589	-0.2552	-0.0842	-0.4866
			RHOEN-KLINIKUM	BMW PREF.	VOSSLOH	HSBC TRINKAUS
	open		5/15/96	5/2/97	5/8/98	5/21/99
	close		6/5/96	8/18/97	6/23/98	4/29/00
	return		-0.0953	-0.0886	-0.0304	0.4384
	CDAX		0.0136	0.1474	0.0578	0.3665
	return - CDAX		-0.1089	-0.2359	-0.0882	0.0719
			RHOEN-KLINIKUM PREF.	FRESENIUS		HYMER
	open		5/14/96	4/1/98		8/19/99
	close		6/5/96	4/29/98		4/29/00
	return		-0.0920	0.0234		0.0514
	CDAX		0.0136	-0.0050		0.3785
	return - CDAX		-0.1056	0.0284		-0.3270
				FRESENIUS PREF.		
	open			3/31/98		
	close			4/29/98		
	return			0.0659		
	CDAX			0.0040		
	return - CDAX			0.0619		
				HEIDELBERGCEMENT		
	open			5/7/97		
	close			12/19/97		
	return			-0.0941		
	CDAX			0.1090		
	return - CDAX			-0.2031		
				MLP		
	open			5/21/97		
	close			4/29/98		
	return			0.7011		
	CDAX			0.3477		
	return - CDAX			0.3534		
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
Short			BHSTABLETOP	HOLZMANN PHILIPP	KENVELO	M-TECH TECH PREF.
	open		5/21/96	1/22/98	7/16/98	4/30/99
	close		4/29/97	2/2/98	4/29/99	6/10/99
	return		-0.3104	0.1008	-0.2958	0.0947
	CDAX		0.2823	0.0492	-0.1262	-0.0342
	return - CDAX		-0.5928	0.0515	-0.1696	0.1289
				ADLER REAL ESTATE		
	open			12/3/97		
	close			4/29/98		
	return			0.0391		
	CDAX			0.2311		
	return - CDAX			-0.1919		
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					
	open					
	close					
	return					
	CDAX					
	return - CDAX					

	2000	2001	2002	2003	2004
Long					
	BHW HOLDING	SCHLOTT GRUPPE	GARANT SCHUH PREF	STADA ARZNEIMITTEL	
open	6/5/00	5/4/01	7/9/02	5/5/03	
close	4/29/01	6/21/01	7/12/02	3/19/04	
return	0.5850	-0.1205	-0.0959	-0.0814	
CDAX	-0.2180	0.0013	-0.0511	0.2647	
return - CDAX	0.8030	-0.1218	-0.0448	-0.3461	
	CONCORD EFFEKTEN		PUMA	TARKETT	
open	5/2/00		6/11/02	5/12/03	
close	5/26/00		7/8/02	4/29/04	
return	-0.1378		-0.0881	0.5786	
CDAX	-0.0961		-0.0313	0.3502	
return - CDAX	-0.0417		-0.0567	0.2284	
	MLP			WELLA	
open	7/6/00			5/28/03	
close	12/1/00			7/25/03	
return	-0.0867			-0.0849	
CDAX	-0.1088			0.1377	
return - CDAX	0.0221			-0.2226	
	ZAPF CREATION			WELLA PREF.	
open	5/4/00			8/28/03	
close	5/11/00			4/29/04	
return	-0.1007			0.1409	
CDAX	-0.0240			0.1436	
return - CDAX	-0.0766			-0.0027	
open					
close					
return					
CDAX					
return - CDAX					
open					
close					
return					
CDAX					
return - CDAX					
open					
close					
return					
CDAX					
return - CDAX					
open					
close					
return					
CDAX					
return - CDAX					
Short					
	BETA SYSTEMS	KLEINDIENST DATEN	GOLD-ZACK	BRILLIANT	DBV-WINTERTHUR HLDG
open	6/8/00	7/2/01	5/7/02	5/7/03	8/25/04
close	4/29/01	11/13/01	4/29/03	7/14/03	9/14/04
return	-0.2140	0.1081	-0.7885	0.1333	0.0943
CDAX	-0.2064	-0.1660	-0.3858	0.1159	0.0399
return - CDAX	-0.0076	0.2741	-0.4026	0.0174	0.0544
	COMPUTEC MEDIA	COMPUTEC MEDIA	M & S ELEKTRONIK	VIVANCO GRUPPE	DUERKOPP ADLER
open	5/24/00	6/20/01	5/3/02	6/12/03	3/10/05
close	4/29/01	4/29/02	6/4/02	6/13/03	3/31/05
return	-0.6804	-0.6033	0.6000	0.1143	0.1207
CDAX	-0.1459	-0.1275	-0.0502	-0.0139	0.0012
return - CDAX	-0.5345	-0.4758	0.6502	0.1282	0.1195
	KAUFRING	PORTA SYSTEMS	PORTA SYSTEMS	WCM BETEILIGUNG	WCM BETEILIGUNG
open	7/13/00	5/8/01	5/7/02	11/5/03	2/25/05
close	4/29/01	5/11/01	5/8/02	4/29/04	2/28/05
return	-0.0278	0.0937	0.1111	-0.2318	0.0978
CDAX	-0.1853	0.0019	0.0244	0.0728	0.0011
return - CDAX	0.1575	0.0919	0.0867	-0.3046	0.0967
		SOFTMATIC	WALTER BAU		MARBERT
open		7/23/01	4/30/02		4/30/04
close		7/26/01	5/6/02		5/6/04
return		0.2111	0.1250		0.1429
CDAX		-0.0134	-0.0251		-0.0197
return - CDAX		0.2245	0.1501		0.1625
			WALTER BAU PREF.		PLAMBECK NEUE ENGE.
open			4/30/02		5/4/04
close			5/6/02		5/6/04
return			0.1386		0.0887
CDAX			-0.0251		-0.0212
return - CDAX			0.1637		0.1098
					ROSENTHAL
open					1/21/05
close					1/28/05
return					0.1587
CDAX					-0.0037
return - CDAX					0.1624
					WINTER
open					5/18/04
close					5/24/04
return					0.1358
CDAX					0.0002
return - CDAX					0.1356

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