Stockholm School of Economics
Department of Finance – Master's Thesis
Spring 2011

An Investment-Based Factor Model

- An Empirical Assessment of a Neoclassical Asset Pricing Model's Relative Pricing Ability on Swedish Stock Return Data

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ABSTRACT

The pursuit of the factors determining the cross-section of average stock returns has traditionally been focused around factors believed to proxy for common sources of risk. Previous research points out that linear factor models built on this approach demonstrate an inadequate pricing ability in a Swedish setting. Opposing the traditional view, investment-based asset pricing instead explains stock returns using factors based on the economic characteristics of firms. Using an extended data set with a reduced survivorship bias we run a horse race between an investment-based asset pricing model and a set of acknowledged benchmark models. The investment-based factor model used is a somewhat modified version of the alternative three-factor model presented by Chen, Novy-Marx & Zhang (2010), and includes an investments-to-assets factor and a return-on-assets factor in addition to the market factor. We apply a time-series regression approach with monthly returns from July 1989 to January 2011 for Swedish stocks listed on the NASDAQ OMX Stockholm. In addition, we examine the individual pricing ability of the factors included in the investment-based model and conclude whether they demonstrate explanatory power not captured by the market factor. Our mixed results show that the investment-based factor model outperforms in terms of pricing ability when applied to test portfolios sorted on return-on-assets ratio. When test portfolios instead are double sorted on size and book-to-market ratio the benchmark models still prevail. In general, the benchmark models show a decent pricing ability, predominantly channeled through the market factor. Lastly, we highlight the usefulness of a proposed two-factor model where the return-on-assets factor is used solely together with the market factor.

Tutor: Assistant Professor Francesco Sangiorgi.

Discussants: Anna Andersson and Sofie Bengtsson.

Date and time: June 1st 2011, 15:15.

Venue: Stockholm School of Economics, room 328.

Acknowledgements: We would like to thank our tutor Francesco Sangiorgi for his continous guidance and advice during the process of writing this thesis. We are also grateful to Mårten Strömberg for valuable comments. All remaining errors are our own.

Contents

1 Introduction

The search for the factors that determine the cross-section of stock returns is probably as old as the field of finance itself. This quest for the "grail" of financial markets has provided us with numerous asset pricing models. For a long period of time Sharpe (1964) and Lintner's (1965) Capital Asset Pricing Model ("CAPM") was considered the answer to the question. As a theoretical model the CAPM is compelling since it explains the cross-section of stock returns with just one factor, beta (β), the extent to which a stock and the market move together. Although theoretically persuasive, numerous empirical tests of the model have pointed out several shortcomings and inconsistencies of the CAPM. In 1993 Fama & French (1993) published their prominent three-factor model in which two factors based on size and book-to-market were added to the market factor. Their findings on U.S. data showed that their model explained the cross-section of stock returns better than the market beta alone. However, also the Fama French three-factor model has been criticized. Some researchers, such as Black (1993), have questioned the findings and the theory behind the proposed factors whereas others have found anomalies that the model cannot explain, such as Jegadeesh & Titman's (1993) momentum observation.

A rapidly expanding field within asset pricing is the investment-based asset pricing. Its foundations are old and can be said to date all the way back to Fischer (1930), but despite having old roots the investment-based approach has historically been scarcely researched. In investment-based asset pricing expected returns are explained by production factors such as investments and output, which is in contrast to for example the Fama French three-factor model where the factors are interpreted as risk factors believed to proxy for common sources of risk.

In a much noted working paper Chen, Novy-Marx & Zhang ("Chen et al.") (2010) propose "An alternative three-factor model" built on investment-based asset pricing. The authors propose an investments-to-assets factor and a return-on-assets factor in addition to the market factor. They test their model on U.S. data for the period 1972 to 2009 and find that the model generally shows better pricing ability compared to the Fama French three-factor model. This is particularly the case when test portfolios are formed based on highlighted anomalies of the Fama French three-factor model.

To our knowledge an investment-based asset pricing model has never been tested on Swedish stock return data. We therefore feel that it would be stimulating and conducive to apply a somewhat modified version of Chen et al.'s (2010) alternative three-factor model in a Swedish setting (model modifications are made primarily for data-availability reasons, for details see *5.5.3 How Our Alternative Three-Factor Model Differs*). It is especially interesting to test a version of this asset pricing model on Swedish data given its strong performance on U.S. data and the poor results of the

CAPM, the Fama French three-factor model and the Carhart four-factor model in empirical tests on Swedish data recently presented by Poutiainen & Zytomierski (2010).

The purpose of this thesis is therefore to contribute to the horse race literature of asset pricing models and test whether our slightly modified alternative three-factor model demonstrates a higher pricing ability compared to the acknowledged models the CAPM, the Fama French three-factor model and the Carhart four-factor model. In order to keep a stringent benchmark when comparing the models we aim to replicate the CAPM, the Fama French three-factor model and the Carhart four-factor model using our data set as previous studies on Swedish data have either suffered from insufficient data or not been adjusted for survivorship bias. Two aspects will thus constitute our contribution to the research of asset pricing in Sweden: testing an investment-based asset pricing model on Swedish data as well as testing the traditional models on a more extensive Swedish data set. The data set is more extensive in the sense that it is, to the best of our ability, adjusted for survivorship bias and (or) is covering a longer period of time.

1.1 Definitions and Clarifications

Below we define and clarify key concepts used throughout the thesis.

» Anomalies are defined as “cross-sectional and time-series patterns in security returns that are not predicted by a central paradigm in theory”. Anomalies are often interpreted as evidence against market efficiency. This is an unsuitable conclusion as the anomaly might be due to an incorrect equilibrium model (Keim, 2008). Accordingly we refer to something as being an anomaly when a cross-sectional or time-series pattern in security returns is not explained by the model in question.

» Investment-based asset pricing is sometimes also referred to as production-based asset pricing. We however use the term investment-based asset pricing exclusively (for a further discussion see section *2.2 Investment-Based Asset Pricing*).

» Cross-sectional security return variation is an observation of varying returns across different securities at a defined point in time.

» Time-series security return variation is an observation of varying returns of a single security over multiple time periods.

1.2 Disposition

This thesis is structured as follows. Section 2 deals with the theoretical framework as well as the previous research in the field of asset pricing and especially investment-based asset pricing. In Section 3 we present our hypotheses and their economic intuitions. Section 4 is designated to describe the data used in this study, how it was retrieved and what necessary adjustments we have made. In section 5 we describe our methodology used when forming explanatory and dependent variables and running regressions. Following that, we present, interpret and discuss our results in section 6. Section 7 is devoted to conclusions and here we also highlight issues suitable for further research. Finally section 8 covers our references. Throughout the thesis an inquisitive reader is referred to the appendices for supplementary data.

2 Literature Review and Theoretical Framework

2.1 Asset Pricing Models

The CAPM was introduced in articles by Sharpe (1964) and Lintner (1965) and defines the origin of asset pricing theory. The model is based on the portfolio selection concept developed by Markowitz (1959) in which investors are expected to be risk averse and only care about the mean and variance of their investments. Investors therefore hold mean-variance efficient portfolios that, through diversification, maximize the return for a given level of risk. The CAPM extension of this idea was that given the same opportunity set all investors must hold the same portfolio of risky assets, known as the market portfolio. An individual asset's weight in this portfolio is thus its market value divided by the market value of all risky assets (Fama & French, 2004). Furthermore, the risk premium of an individual asset in this setting is proportional to the risk premium of the market portfolio and the extent to which the asset and the market move together, known as the asset's market beta (Bodie et al., 2008). More formally, asset i's market beta is given by equation (1):

$$\beta_{iM} = \frac{cov(R_{i,}R_M)}{\sigma^2(R_M)} \tag{1}$$

where the covariance of the return of asset i with the market return is divided by the variance of the market return. Adding the assumption of risk-free lending and borrowing to this idea gives us the Sharpe-Lintner CAPM equation:

$$E[R_i] - R_f = \beta_{iM}(E[R_M] - R_f) \tag{2}$$

where the expected return of the risky asset i, $E[R_i]$, in excess of the risk-free interest rate, R_f, equals a risk premium, which is given by the excess return of the market, $E[R_M] - R_f$, times the asset's market beta, β_{iM} (Fama & French, 2004).

In this way the CAPM provides a model that explains the cross-sectional difference in stock returns with market beta as the only factor. Being a rather simple model and based on strong assumptions the

CAPM has been intensively tested since it was first published. More empirical effort may have been put into testing the CAPM equation than any other result in finance (Rubinstein, 2006).

Early empirical tests of the CAPM such as Black, Jensen & Scholes (1972) and Fama & MacBeth (1973) found some support for the model. Black, Jensen & Scholes (1972) found a positive linear relationship between return and beta on data from NYSE for the period 1931 to 1965 for ten portfolios sorted on beta. However the slope and the intercept were significantly different from their theoretical values which made the authors conclude that the model's predictions were consistent with the data remembering that the CAPM only is an approximation of reality. Fama & Macbeth (1973) used data from NYSE for the period 1926 to 1968 and also found that data in general supported the model (Jagannathan & McGrattan, 1995).

Banz (1981) tested the validity of the CAPM by investigating whether size, as measured by a firm's market value of equity, could explain residual variation in stock returns not captured by beta. Banz found that firms with a small market value of equity had significantly larger risk adjusted returns than large firms on the NYSE during the years 1936 to 1975. This anomaly, which suggests that the CAPM is miss-specified, is known as the size effect (Jagannathan & McGrattan, 1995).

Stattman (1980) and also Rosenberg, Reid & Lanstein (1985) documented another anomaly of the CAPM. They found that U.S. stocks with high book-to-market ratios had higher average returns than predicted by their betas (Fama & French, 2004). Rosenberg, Reid & Lanstein's (1985) study consisted however only of data from a rather short time period, 1973 to 1984, which limited the attention their article received after being published (Davis, 2001). Chan, Hamao & Lakonishok (1991) also documented a significant cross-sectional relationship between book-to-market and returns on Japanese data for the period 1971 to 1988.

Building on the work of Banz (1981), Stattman (1980) and Rosenberg, Reid & Lanstein (1985), Fama & French (1992) further questioned the validity of the CAPM in what became a very influential paper using the two-pass cross-sectional regression approach outlined by Fama & MacBeth (1973). In 1993 Fama & French (1993) proposed a three-factor model that in addition to the market factor also includes a size and a book-to-market factor. They measured the size factor as the difference in return in each period between small firms and large firms, giving the factor its name "small minus big" or SMB. Correspondingly, the book-to-market factor was measured as the difference in returns of firms with high book-to-market ratios and firms with low book-to-market-ratios, named "high minus low" or HML (Bodie et al., 2008). The presented Fama French three-factor equation (3) is outlined below:

$$E[R_i] - R_f = \beta_{iM}\left(E[R_M] - R_f\right) + \beta_{iSMB}E[SMB] + \beta_{iHML}E[HML] \tag{3}$$

By evaluating their model on data from NYSE, AMEX and NASDAQ for the period 1963 to1990 they found a strong relation between average stock returns and the size and book-to-market factors. In contrast to the CAPM they found that after controlling for size and book-to-market, beta did not seem to have any power in explaining average returns (Fama & French, 1993).

As the CAPM, the Fama French three-factor model has been intensively tested and questioned since it was first published. Black (1993) argued after studying the data and results of Fama & French (1992) that the size effect disappeared after it was first found by Banz (1981), since the effect was absent in their data from 1981 to 1990. He also questioned the lack of theory behind the proposed factors. Others have found anomalies not captured by the Fama French three-factor model. Examples include Jegadeesh & Titman's (1993) momentum observation and Chan, Jeegadeesh & Lakonishok's (1995) earnings surprise effect. The Fama French three-factor model has been tested on Swedish data by Bergström & Rustam (2010) and by Poutiainen & Zytomierski (2010) with mixed results. Issues somewhat undermining their studies are a limited data set and an absolute survivorship bias respectively.

Building on the momentum anomaly observed by Jegadeesh & Titman (1993), Carhart (1997) developed a four-factor model that added a momentum factor, PR1YR, to the Fama French three-factor model. Carhart (1997) defined the momentum factor, PR1YR, as the difference in returns of firms with the highest 30% eleven-month returns lagged one month minus the firms with the 30% lowest eleven-month returns lagged one month. His model is specified as:

$$E[R_i] - R_f = \beta_{iM}\left(E[R_M] - R_f\right) + \beta_{iSMB}E[SMB] + \beta_{iHML}E[HML] + \beta_{iPR1YR}E[PR1YR] \qquad (4)$$

Carhart (1997) found that this four-factor model significantly reduced the average pricing errors in the CAPM and the Fama French three-factor model, thereby demonstrating that it better described the cross-section of average stock returns. As with the Fama French factors the theoretical basis of the momentum factor is rather vague and is primarily regarded as an empirical observation. Even Jegadeesh & Titman (1993), who found the effect, were unsure of how to interpret their momentum finding but proposed a behavioral explanation in the form of short-term investor under-reaction.

2.2 Investment-Based Asset Pricing

A growing field within asset pricing is the so called investment-based asset pricing. The idea and implications of investment-based asset pricing differ significantly from influential asset pricing models such as the CAPM and the Fama French three-factor model. Because where the latter two models interpret their factors as risk factors proxying for common sources of risk, the investment-based approach bases its factors on firm characteristics such as the level of investments and production, and suggests that this is what explains returns. Put differently, investment-based factors can be said to explain returns not because they necessarily are risk factors but because they are based on firms' economic fundamentals (Chen et al., 2010). This also implies that risk is not automatically the goal of asset pricing in the investment-based approach, instead risk and expected returns are considered endogenous variables jointly determined in equilibrium, where neither is more primitive than the other. Basing the analysis on observable firm characteristics, as the investment-based approach does, also connects asset pricing more to the traditional fields of securities valuation and corporate finance (Zhang, 2010). In our view this is an interesting and reasonable link, because if firms can be valued based on their characteristics it is not far-fetched to believe that returns also could be inferred from the same sources.

The theoretical foundations of investment-based asset pricing are old and analogous to those of the consumption-based asset pricing. It was Fischer (1930) who first constructed an intertemporal general equilibrium model in which he found two explanations of the interest rate, consumer preferences and productivity (see Equation A1 in the appendix for a thorough derivation of Fischer's model). Asset pricing theory from the 1970s to the 1990s focused however on the part covering consumer preferences in various consumption-based asset pricing models, such as Breeden's (1979) and Lucas's (1978) Consumption Capital Asset Pricing Model (Zhang, 2010).

In 1991 Cochrane (1991) proposed an investment-based asset pricing model in which stock returns were linked to investment returns. The somewhat simple idea of the model was that stock returns and investment returns should be equal. The empirical findings of the model were that forecasts of investments and stock returns appeared to be the same and that historical investment returns and stock returns seemed highly correlated. However, Cochrane's model performed poorly in explaining the component of stock returns forecastable by dividend-price ratios. Building on the work of Cochrane (1991), Liu, Whited & Zhang (2009) showed, in accordance with Fischer's finding, that stock returns can be linked to the production side and factors such as the capital's share in output, the investment-to-capital ratio, the sales-to-capital ratio and market leverage (see Equation A2 in the appendix). Liu, Whited & Zhang (2009) also tested their model empirically and found that it explained relations between stock returns and earnings surprises, book-to-market ratios and corporate investments, areas in which the consumption-based models previously had performed poorly (Zhang, 2010).

Titman, Wei & Xie (2004) empirically found a negative relation between investments and future stock returns on U.S. equities during the years 1973 to 1996. The authors stressed the fact that increased investments in theory can be both favorable and unfavorable. The favorable aspect is that firms investing more are likely to have better investment opportunities. The unfavorable characteristic is that firms investing more tend to be managed by individuals who have a tendency to overinvest (the so called empire-builders). Given their empirical observation of a negative investment-return relationship their findings indicated that the latter on average was the case in reality. Furthermore, they also found that the only period the negative relation between investments and stock returns failed to exist in their sample was between 1984 and 1989. This was a period characterized by hostile takeovers that probably disciplined managers and firms that overinvested.

In a current working paper Chen et al. (2010) propose an alternative three-factor model based on previous findings in the field of investment-based asset pricing. They form a multifactor model with an INV and a ROA factor, based on the investments-to-assets ratio and return-on-assets ratio. In addition they also include the CAPM market factor from the consumption side of the economy. Following Titman, Wei & Xie's (2004) negative investment-return relationship the INV factor is defined as the return of a portfolio consisting of low-investment firms minus the return of a portfolio consisting of high-investment firms. The ROA factor is based on the difference in return between a portfolio consisting of firms with high return-on-assets ratios and firms with low return-on-assets ratios. Their model is formally given by equation (5).

$$E[R_i] - R_f = \beta^i_{MKT}\left(E[R_{MKT}] - R_f\right) + \beta^i_{INV}E[R_{INV}] + \beta^i_{ROA}E[R_{ROA}] \tag{5}$$

In their sample period from January 1972 to June 2009 they show that the new alternative three-factor model in general outperforms old factor models such as the Fama French three-factor model in terms of pricing ability for a long array of test portfolio sorting procedures. Among these sorting procedures are many known Fama French anomalies such as for example, earnings surprises, total accruals and asset growth.

3 Hypotheses

3.1 Hypothesis 1

A multifactor asset pricing model including two independent variables based on the firm characteristics investments-to-assets ratio and return-on-assets ratio, in addition to the market factor, can better explain the cross-section of Swedish average stock returns compared to the CAPM, the Fama French three-factor model and the Carhart four-factor model.

3.1.1 Intuition Hypothesis 1

Chen et al.'s (2010) alternative three-factor has demonstrated strong performance on U.S. data. Simultaneously, evidence of poor performance of the CAPM, the Fama French three-factor model and the Carhart four-factor model with respect to Swedish stock returns has been presented by Poutiainen & Zytomierski (2010). This leads us to believe that our slightly modified investment-based model is a better alternative for explaining the cross-section of average stock returns on Swedish data. In order to keep a stringent benchmark when comparing the models we also aim to replicate the CAPM, the Fama French three-factor model and the Carhart four-factor model on our Swedish data set as previous studies doing this have either suffered from insufficient data or have not made adjustments for survivorship bias. By doing so we can also determine if the traditional models' deficient pricing ability outlined in previous research indeed is the case also in our more extensive data set.

3.2 Hypothesis 2

An independent variable based on the firm characteristic investments-to-assets ratio demonstrates a pricing ability that is not captured by the market factor.

3.2.1 Intuition Hypothesis 2

The idea that such a factor is priced in an asset pricing model and has explanatory power with respect to the cross-section of Swedish average stock returns is based on the empirical evidence presented by Titman, Wei & Xie (2004). Their findings indicate a negative effect on stock returns from exploiting too many investment opportunities and we expect to find that average returns decrease with the investments-to-assets ratio. This implies that we expect Swedish firms with low investments-to-assets ratios to have higher average stock returns than Swedish firms with high investments-to-assets ratios. We believe that a factor based on the firm characteristic investments-to-assets ratio should proxy for a common characteristic, which can explain differences in average returns between stocks. The negative relation between expected returns and investments is probably most intuitive from a capital budgeting point of view. A firm that faces high costs of capital (implicitly high expected returns) will have low net present values of new projects and therefore invest less. In contrast, a firm with low costs of capital (implicitly low expected returns) will observe high net present values of new projects and therefore invest more (Chen et al., 2010).

3.3 Hypothesis 3

An independent variable based on the firm characteristic return-on-assets ratio demonstrates a pricing ability that is not captured by the market factor.

3.3.1 Intuition Hypothesis 3

We expect to find that such a factor is priced in an asset pricing model and has explanatory power with respect to the cross-section of Swedish average stock returns and that stock returns increase with the return-on-assets ratio. This implies that Swedish firms with high return-on-assets ratios should have higher returns than Swedish firms with low return-on-assets ratios. We believe that a factor based on the firm characteristic return-on-assets ratio should proxy for a common characteristic, which can explain differences in average returns between stocks. That the return-on-assets ratio, being a profitability indicator ratio, is related to expected returns is based on the idea that more profitable firms earn higher expected returns. The intuition behind this relationship can perhaps easiest be understood from traditional discounted cash flow models such as the Dividend Discount Model. In the Dividend Discount Model the value of a stock equals the present value of expected future dividends. Future dividends are the results of the cash flows a company will be able to generate in the future. Intuitively, a more profitable firm will generate stronger cash flows and thereby be able to provide higher dividends to its shareholders. This entails that expected profitability is related to expected returns. Even Fama & French (2006) stress, in a paper being based on traditional valuation theory, that expected stock returns are related to the three variables: the book-to-market ratio, the expected profitability and the expected investment. They also find support for this idea empirically. However their profitability indicator ratio is not the same as ours, because where our measure is based on the return on total assets their measure is based on the return on the book value of equity.

4 Data

4.1 Sample Selection

Our initial data set consists of all stocks listed on the NASDAQ OMX Stockholm[1] as of the last trading day in January 2011 as well as delisted firms for the period January 1st 1986 to January 1st 2011. These are (were) the stocks listed on the main stock exchange and together they form (formed) the basis for the OMX Affärsvärlden's General Index (OMX AFGX), the benchmark index we use as our market proxy. The set of stocks listed on the NASDAQ OMX Stockholm at the end of January 2011 was retrieved from NASDAQ OMX Nordic (2011). Information regarding the delisted firms was partly acquired from NASDAQ OMX Trader (2010), in the annual fact books and data statistics from 1996 to 2010. Prior to 1996 Sundin (1987-1993) and Sundin & Sundqvist's (1994-1996) annual summary over Swedish listed firms and their owners were used to find information about the firms that had been delisted each year. The required data for each company, returns (monthly), market capitalization (monthly) and accounting measures (annual), was retrieved from Thomson Reuters Datastream ("Datastream") and Standard & Poor's Compustat ("Compustat").

As we aim to evaluate an investment-based factor model and contrast its pricing ability to the benchmark models the CAPM, the Fama French three-factor model and the Carhart four-factor model we need data for a number of accounting variables. For the variables we are interested in Datastream has the most extensive database. We therefore make our initial data extraction from Datastream and thereafter complement it with data from Compustat where possible in order to get the most comprehensive data set. All data was retrieved during January 2011. Market capitalization and

[1] And its predecessors "StockholmsFondbörs", "OM Stockholmsbörsen" and "OMX Stockholmsbörsen".

Datastream's total return index is extracted at month-end for each firm. The annual accounting data extracted for each firm include: total assets, total inventories, total gross property, plant and equipment ("GPPE"), net income before extraordinary items and book value of equity (see Table B1 for the exact Datastream mnemonics and Compustat items used).

For measuring market capitalization, we use Datastream's item market value, which is defined as the share price times the number of ordinary shares in issue. This item in Datastream is defined on a security level and not on a company level, implying that it does not capture the true market capitalization of companies with more than one class of shares. Unfortunately Datastream does not offer any time-series version of market value at the company level with the required monthly frequency. Given that companies with more than one class of shares are rather common among blue-ships in Sweden (with the use of shares with different voting rights such as A and B shares), we choose to sum the market value over each class of shares for the 49 firms in our sample with more than one publicly traded share.

Data for the value-weighted OMX AFGX was retrieved from Affärsvärlden (2011). As proxy for the risk-free rate of return we use a monthly average of the Stockholm Interbank Offered Rate with one-month maturity, STIBOR 1M. This data was retrieved from the Riksbank (2011).

4.2 Sample Adjustments

4.2.1 Omitted Data

We impose the following data-availability requirement all firms need to fulfill in order to be included in the annual rankings (for details regarding ranking procedures, see *5.5 Calendar-Time Factor Regressions*) we perform each year t at the end of June: total return index at the end of June $t-1$, market capitalization at the end of December $t-1$ and at the end of June t, total assets for $t-1$ and $t-2$, total inventories for $t-1$ and $t-2$, total GPPE for $t-1$ and $t-2$, net income before extraordinary items for $t-1$ and a positive book value of equity for $t-1$.

Although somewhat stringent, the above requirement is imposed for consistency reasons. The main implication of the requirement is that if a firm is included in the sorting procedures at the end of June a given year, it is included in all test portfolios and in all factor models resulting in more comparable results. The implication of the last part of the requirement is that we exclude firms in our analysis from July year t to June year $t+1$ if they have a negative book value of equity in year $t-1$. Although there are only eight yearly observations with negative book value of equity in our data set, these are excluded due to the doubtful economical meaning.

Our original data set included 780 firms, 255 listed on the NASDAQ OMX Stockholm and 525 firms delisted sometime during our sample period. Many of the firms, mostly the delisted, have missing or insufficient data in Datastream and Compustat and are therefore excluded. In accordance with Fama & French (1993) we also clear our data set from Depositary Receipts (SDRs), i.e. companies that are not based in Sweden and report in another currency than SEK. However, in contrast to Chen et al. (2010) and Fama & French (1992) we decide to keep financials with sufficient data. Barber & Lyon (1997) show that the conclusions regarding size, book-to-market ratio and security returns are similar for financial and non-financial firms, and in order to keep as many data points as possible we therefore include financials in our data set. We tackle the issue with some companies having more than one listed class of shares by only including one share per firm (i.e. only the A, B or C share) in order to avoid duplicates. When deciding which share to keep we consider the total return index, which is the only variable with potential relevant differences between the issues. By studying differences in the trading liquidity of the issues based on their average trading volume we choose to include the share of each company showing the highest average trading volume. This should intuitively reflect the most accurate theoretical return of the company.

Due to limited historical data prior to 1989, we decide to do our first annual rankings at the end of June 1989. The reason is that by including years with data covering only a few firms the relative importance of each firm increases and with that the unwelcome risk of magnifying outliers' impact on the end results.

4.2.2 Survivorship Bias

We reduce a potential survivorship bias in our data set by initially adding back all delisted firms during the time period July 1st 1989 to January 31st 2011. However only 191 out of the 525 delisted firms have sufficient data in Datastream and Compustat, leaving a fair amount of delisted firms out. This implies that our data set does undeniably suffer from a survivorship bias to a certain degree. However, it is, in contrast to previous studies on Swedish data, far from an absolute survivorship bias. Worth noting regarding the data of the delisted firms is also that the data-availability is scarcer further back in time and poorer among smaller firms. This indicates that the survivorship bias probably is more severe earlier on in our sample period and also more substantial among smaller firms.

4.3 Final Sample

After adjusting our data set as described above in *4.2.1 Omitted Data* our final sample consists of 214 active and 191 delisted firms, 405 firms in total. It varies from a minimum of 40 firms during 1989 to 245 firms in June 2002, with a monthly average of 171 firms. From 1989 to 2003 the annual average number of included firms steadily increases to thereafter slightly decrease down to 215 in 2010. A consequence of conducting our first ranking at the end of June 1989 is that our data set of monthly returns begins in July 1989. We conduct our last ranking at the end of June 2010 and our last observations of monthly returns are from January 2011. This totals 259 months and 44283 monthly firm observations. Table B2 presents the names of the firms we include in our study and Table B3 presents the names of the firms we exclude together with the reason for exclusion.

5 Methodology

5.1 The Relevant Linear Factor Models

We are primarily interested in studying if an investment-based factor model can reduce on the mispricing, given certain Swedish test portfolios, compared to the acknowledged benchmark models. Theoretically, our slightly modified version of Chen et al.'s alternative factor model (6) and the competing benchmark factor models the CAPM (7), the Fama French three-factor model (8) and the Carhart four-factor model (9) are given by:

$$E[R_i^e] = \alpha_i + \beta_{iM}E[R_M^e] + \beta_{iINV}E[INV] + \beta_{iROA}E[ROA] \tag{6}$$

$$E[R_i^e] = \alpha_i + \beta_{iM}E[R_M^e] \tag{7}$$

$$E[R_i^e] = \alpha_i + \beta_{iM}E[R_M^e] + \beta_{iSMB}E[SMB] + \beta_{iHML}E[HML] \tag{8}$$

$$E[R_i^e] = \alpha_i + \beta_{iM}E[R_M^e] + \beta_{iSMB}E[SMB] + \beta_{iHML}E[HML] + \beta_{iPR1YR}E[PR1YR] \tag{9}$$

where the superscript e denotes excess returns and the intercept α is implied to be zero in all four models.

5.2 The Time-Series Regression Approach

As we intend to contribute to the horse race literature within this field of linear factor models by looking at relative pricing ability it is logical to address the issue of model performance in the time-series dimension as opposed to in the cross-sectional dimension. Implementing a time-series excess return regression analysis is for reasons presented below widely used within this area of research. In accordance with Fama & French (1993), but opposed to Fama & French (1992), we therefore use a multivariate time-series regression approach based on the method presented by Black, Jensen & Scholes (1972) to test our three hypotheses.

When evaluating a given factor model of this kind there are two central questions that are important to distinguish between, namely how well the model explains the cross-section of average returns and how well the model explains the variation in stock returns. Where the former largely is focused on whether or not a model estimates significant intercepts, the latter mainly is a question about factor loading patterns and values of R-squared. Thus, the two central questions constitute different aspects of model performance. However, when it comes to a model's pricing ability both are relevant. The former relates to absolute pricing and is the most important question in this context, but evaluating the latter can broaden the picture of model performance using concepts from relative pricing and the Arbitrage Pricing Theory ("APT"). Throughout this section we describe how the analysis is implemented.

In the time-series regression approach dependent variables, in the form of monthly portfolio returns in excess of a proxy for the risk-free interest rate, are regressed on a set of model-specific independent variables, the so called factors, which are the returns on zero-cost mimicking portfolios. An example of this is the Fama French three-factor model, where the three factors are the market factor which is a zero-cost portfolio invested in the aggregated market portfolio and funded by borrowing at the risk-free interest rate, the size factor which is invested in a portfolio of small-sized firms and funded by shorting a portfolio of large-sized firms and finally the book-to-market factor which is invested in a portfolio of value firms and funded by shorting a portfolio of growth firms. The idea is that the factors should proxy for sensitivity to common characteristics, although not necessarily risk factors, which explain differences in average returns among stocks. The time-series regression shows in a rather simple and direct way if the factors succeed in doing this.

The reason this set-up is convenient is because we only deal with excess returns or returns of zero-cost portfolios. When this is the case the intercept, α, in the regression equation can directly be interpreted as the pricing error of a given asset pricing model. To illustrate this, analogically to the discussion made in Black, Jensen & Scholes (1972), consider the CAPM where the expected return on an arbitrary stock *i* during one time period is given by:

$$E[R_i] = \beta_i E[R_M] \tag{10}$$

and where the following holds:

$$R_i = E[R_i] + \beta_i R_M^* + \varepsilon_i \tag{11}$$

$$R_M^* = R_M - E[R_M] \tag{12}$$

$$E[R_M^*] = 0 \tag{13}$$

$$E[\varepsilon_i] = 0 \tag{14}$$

$$E[R_M^* \varepsilon_i] = E[R_M^*]E[\varepsilon_i] = 0 \tag{15}$$

assuming R_M^* and ε_i are independent, normally distributed random variables. Using equation (10) to substitute for $E[R_i]$ in equation (11) and by using equation (12) yields:

$$R_i = \beta_i R_M + \varepsilon_i \tag{16}$$

which describes the ex-post return from holding stock i during one time period. If this is extended to multiple periods by indexing with t it is possible to test the theoretical model by adding an intercept, α_i, given that equation (10) holds over each short time interval. In our study a time interval would be one month and we would estimate the regression equation:

$$R_{it} = \alpha_i + \beta_i R_{Mt} + \varepsilon_{it} \tag{17}$$

If the model holds perfectly according to equations (10) – (15) the estimated value of α_i equals zero. Put differently, if the estimated value of α_i is not equal to zero, then the factor performs badly in capturing the cross-section of average stock returns and the theoretical model is not valid. Therefore a straightforward way to test this feature is to estimate the regression equation and determine whether or not the value of α_i is statistically different from zero knowing this is true for a well-specified asset pricing model (Merton, 1973). As this reasoning also holds for multifactor models and can be extended to portfolios instead of single stocks, this becomes a handy tool when comparing models (Black, Jensen & Scholes, 1972).

We look at whether or not a given intercept α is significant, i.e. statistically different from zero, by evaluating its test statistic, defined as the estimate over its standard error, in a t-test with the null hypothesis that the intercept equals zero. In line with previous research we exclusively use the 5% significance level. Based on the length of our data set and the fact that no model includes more than four factors, the minimum degrees of freedom used in any given test is 255. Using the t-distribution we therefore consider an intercept as significant if its test statistic fulfills the following condition:

$$|t_{T-K}| \geq 1.97 \tag{18}$$

where T is the length of the time-series and K is the number of independent factors in the regression.

Finally, another feature that makes the time-series regression approach convenient is the way of studying a model's ability to explain variation in returns. By using factors like those described for the Fama French equation above common sources of covariation can be uncovered. More explicitly, if the mimicking portfolios capture shared variation in stock returns not explained by other factors, this is indicated by the regression slopes and the values of R-squared. The regression slopes (the betas) are factor loadings representing the sensitivity with respect to the model factors (Fama & French, 1993).

A model's ability to explain the variation in stock returns is related to its pricing ability through relative pricing and the APT. The better a model's factors succeed in explaining the variation in stock returns the lower the residual sum of squares and the closer the test portfolio returns are to obeying an exact factor structure. Taken to its extreme, when the R-squared equals one and there is no unexplained variance, the intercept has to equal zero or else there is an arbitrage opportunity where the test portfolio can be bought/sold and hedged with a combination of the model factors (Cochrane, 2005). Absence of arbitrage therefore implies that a high level of R-squared puts a theoretical upper bound on the absolute size of the intercept. Thus, a high R-squared value is also an indication of adequate pricing ability.

5.3 Stock Returns and Heteroscedasticity

One of the assumptions underlying the ordinary least squares method of estimating unknown parameters in linear regressions, like the ones we employ, is that the variance of the error term is constant. If indeed the variance of the error term is the same in each time period this is called homoscedasticity, which is desirable from an estimation point of view. However, if this is not the case heteroscedasticity is present which violates the underlying assumption. Although heteroscedasticity does not cause the parameter estimates to be biased, it invalidates the standard errors of the estimates and therefore also the t-test statistics. Stock returns is a textbook example of a case where heteroscedasticity most likely is present, as it has been shown that the volatility of stock returns often depends on past stock returns (Wooldridge, 2008). For that reason we use robust standard errors of the estimates making the t-test statistics adjusted for heteroscedasticity.

5.4 Return Calculations and Value-Weighting

We base our calculations of monthly simple buy and hold returns on Datastream's total return index, which is a compound return index showing the theoretical growth in the value of a stock assuming dividends are re-invested. The index value for trading day t, $DTRI_t$, is given by:

$$DTRI_t = DTRI_{t-1}\left(\frac{P_t + D_t}{P_{t-1}}\right) \tag{19}$$

where P_t is the price on the ex-date, P_{t-1} is the price on the previous day and D_t is the dividend payment on the ex-date.

All time-series of monthly portfolio returns used in our study are value-weighted based on market capitalization, including the data for the market proxy. Although the obvious reason for doing so is due to the replicating feature of our study, it also makes sense given our data set. Table B4 and B7 indicate that within our sample of firms, the standard deviation of monthly returns is generally inversely related to the market capitalization. Therefore, value-weighting the monthly portfolio returns should work to reduce the variance. In addition, value-weighting is also more economically reasonable compared to equal-weighting since it better reflects relative conditions, related to size, on the stock market.

5.5 Calendar-Time Factor Regressions

Even though the theoretical asset pricing models presented above are expressed in terms of expected returns, realized returns are possible to use for an empirical evaluation (Black, Jensen & Scholes, 1972). The benchmark empirical proxy for ex-ante expected returns is average realized returns, despite being pointed out as a noisy proxy in papers by for example Sharpe (1978) and Elton (1999). As we intend to empirically test a set of traditional factor models in addition to our slightly modified version of the alternative three-factor model, this study contains several explanatory variables. A description of all time-series regression equations and their included factors are presented below.

5.5.1 Regression Equations

To empirically test the four linear factor models presented in *5.1 The Relevant Linear Factor-Models* we run the following corresponding four regression equations for each set of test portfolios:

$$R_{it}^{e} = \alpha_i + \beta_{iM} R_{Mt}^{e} + \beta_{iINV} INV_t + \beta_{iROA} ROA_t + \varepsilon_{it} \tag{20}$$

$$R_{it}^{e} = \alpha_i + \beta_{iM} R_{Mt}^{e} + \varepsilon_{it} \tag{21}$$

$$R_{it}^{e} = \alpha_i + \beta_{iM} R_{Mt}^{e} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_{it} \tag{22}$$

$$R_{it}^{e} = \alpha_i + \beta_{iM} R_{Mt}^{e} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iPR1YR} PR1YR_t + \varepsilon_{it} \tag{23}$$

where t = 1, 2, …, 259 months and the interval of i depends on the size of the specific set of test portfolios.

5.5.2 Model Factor Portfolios – The Independent Variables

The Market Factor

The CAPM's only explanatory variable is the market factor, $R_{Mt}^{e} = R_{Mt} - R_{ft}$, which also is included in all the other models. We compute the market risk premium each month as the return on the OMX AFGX minus that month's average STIBOR 1M rate.

SMB and HML

The Fama French three-factor model contains two additional independent variables, small minus big (SMB) and high minus low (HML). We construct the factors following the procedure outlined in

Fama & French (1993). All firms are independently ranked each year at the end of June based on their size and their book-to-market ratio. Given the rankings six portfolios are created and for these, monthly returns are calculated for the consecutive twelve months. The size ranking in June year t is based on the market capitalization in June year t. Given that ranking, the firms are sorted into two portfolios: big (B) consisting of the 50% of firms with the highest market capitalization and small (S) consisting of the 50% of firms with the lowest market capitalization. The book-to-market ranking at the end of June year t is based on the book value of equity in December year $t-1$ divided by the market capitalization in December year $t-1$. Given that ranking firms are sorted into three portfolios: low (L) consisting of the 30% of firms with the lowest book-to-market ratio, medium (M) consisting of the 40% of firms with medium book-to-market ratio and high (H) consisting of the 30% of firms with the highest book-to-market ratio. Following the two rankings, six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) are created at the intersection of the five portfolios S, B, L, M and H. As an example, the portfolio S/H consists of firms characterized by both being small and having the highest book-to-market ratio. Monthly returns are calculated for the six portfolios from July year t to June year $t+1$. The portfolios are thereafter rebalanced at the end of June year $t+1$. Given the six portfolios, the zero-cost portfolios defining the SMB and HML factors are constructed using the following equations:

$$SMB = \frac{(S/L + S/M + S/H) - (B/L + B/M + B/H)}{3} \tag{24}$$

$$HML = \frac{(S/H + B/H) - (S/L + B/L)}{2} \tag{25}$$

The SMB factor is the difference each month between the arithmetic average of returns on three small-firm portfolios and the arithmetic average of returns on three big-firm portfolios. By controlling for differences in the book-to-market ratio, the SMB factor is meant to capture different return behaviors of small and big firms. Similarly, the HML factor is constructed as the difference each month between the arithmetic average of returns on two portfolios consisting of firms with high book-to-market ratio and the arithmetic average of returns on two portfolios consisting of firms with low book-to-market ratio. By controlling for differences in size, the HML factor is designed to capture different return behaviors of firms with high and low book-to-market ratios (Fama & French, 1993).

INV

Besides the market factor, the alternative three-factor model proposed by Chen et al. (2010) consists of the factors INV and ROA. When building both the INV factor and the ROA factor we control for size and the sorting technique used each year at the end of June bears many similarities to the two-by-three sort used by Fama & French (1993). All firms are independently ranked each year at the end of

June based on their size and their investments-to-assets/return-on-assets ratio. Given the rankings six portfolios are created and for these portfolios, monthly returns are calculated for the twelve consecutive months. The portfolios are thereafter rebalanced. The INV factor is constructed in analogy with the method outlined in Chen et al. (2010). The size ranking in June year t is based on the market capitalization in June year t. Given the size ranking firms are sorted into the two familiar size portfolios, S and B. The investments-to-assets ranking in June year t is based on a measure aiming to capture the relative level of investments as the change in long- and short-lived assets relative to the lagged value of total assets and is defined by:

$$I/A_{t\,(Jun)} = \frac{(GPPE_{\,t-1\,(Dec)} - GPPE_{t-2\,(Dec)}) + (Inventories_{t-1\,(Dec)} - Inventories_{t-2\,(Dec)})}{Assets_{t-2\,(Dec)}} \tag{26}$$

Given the I/A ranking, firms are sorted into three portfolios: low (L) consisting of the 30% of firms with the lowest investments-to-assets ratio, medium (M) consisting of the 40% of firms with medium investments-to-assets ratio and high (H) consisting of the 30% of firms with the highest investments-to-assets ratio. Again, six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) are created at the intersection of the five portfolios S, B, L, M and H. Based on the set of these six portfolios, the INV factor is constructed as:

$$INV = \frac{(S/L + B/L) - (S/H + B/H)}{2} \tag{27}$$

Hence, the INV factor is the difference each month between the simple average of returns on two portfolios consisting of low-investment firms and the simple average of returns on two portfolios consisting of high-investment firms. The logical reason for controlling for size stems from empirical findings by Fama & French (2008) showing that the asset growth anomaly is significant for small firms whereas it is essentially nonexistent for large firms. Since asset growth is a broad measure of investments, controlling for size differences seems reasonable. By doing this the INV factor is designed to capture different return behaviors of firms with low and high levels of investments.

ROA

The construction of the ROA factor is similar to that of the INV factor. For the ROA factor the independent rankings are based on size and the return-on-assets ratio and designed to capture different return behaviors of firms with high and low return-on-assets ratios. The return-on-assets ratio (R/A) the firms are being ranked upon in June year t is defined as:

$$R/A_{t\,(Jun)} = \frac{Net\ income\ before\ extraordinary\ items_{t-1\,(Dec)}}{Assets_{t-2\,(Dec)}} \tag{28}$$

This implies that when constructing the ROA factor we make slight modifications to the method outlined by Chen et al. (2010). They base their return-on-assets measure on quarterly accounting data and rebalance the portfolios monthly. We instead base our return-on-assets measure on annual data and apply annual rebalancing on the portfolios. In contrast to the abundant availability of accounting data for U.S. firms, the availability of Swedish interim accounting data is extremely limited. Datastream and Compustat only have historic interim data starting from approximately 2001 and this data is limited and covers mostly large caps.[2] Therefore, to only use quarterly data for the ROA factor would make the data set too small given our data-availability requirement. Moreover, we also rule out the option of using whatever interim data available, as this would bias the ROA factor since the average return-on-assets ratio is notably higher for large firms compared to small firms in our data set. In pursuing a consistent test of asset pricing models over an extended period of time we proceed with annual data also for the ROA factor. We believe this is less of a problem as Chen et al. (2010) point to the fact that the return-on-assets ratio is highly persistent over time. Based on a corresponding set of six portfolios (S/L, S/M, S/H, B/L, B/M and B/H), the ROA factor is given by:

$$ROA = \frac{(S/H + B/H) - (S/L + B/L)}{2} \tag{29}$$

Intuitively, the ROA factor is the difference each month between the simple average of returns on two portfolios consisting of firms with high return-on-assets ratios and the simple average of returns on two portfolios consisting of firms with low return-on-assets ratios. By controlling for differences in size, the ROA factor is designed to capture different return behaviors of firms with high and low return-on-assets ratios.

PR1YR

In addition to the factors in the Fama French three-factor model, the Carhart four-factor model also includes PR1YR, a factor mimicking one-year momentum in stock returns. We construct the momentum factor in accordance with Carhart (1997). At the end of each month t, all firms are ranked based on their eleven-month return lagged one month. More specifically, the momentum measure for month t, in terms of Datastream's total compound return index, is given by:

$$Momentum_t = \frac{DTRI_{t-1}}{DTRI_{t-12}} - 1 \tag{30}$$

The PR1YR factor is the difference each month between the return of a portfolio consisting of the 30% of firms with the highest momentum measure and the return of a portfolio consisting of the 30% of firms with the lowest momentum measure. The portfolios are rebalanced monthly.

[2] The authors are grateful to Hanna Setterberg at the Department of Accounting at the Stockholm School of Economics for guidance on interim accounting data on Swedish companies.

5.5.3 How Our Alternative Three-Factor Model Differs

For various reasons our slightly modified version of the alternative three-factor model differs somewhat from the original presented by Chen et al. (2010). Apart from a bit altered notation, the model-specific differences are the following:

- as opposed to quarterly accounting data for the ROA factor we use annual accounting data
- as opposed to monthly rebalancing of the ROA factor we use annual rebalancing
- as opposed to only using Compustat data, we use data from both Compustat and Datastream
- as opposed to excluding all financial firms we include firms from all industries
- we impose a more stringent data-availability requirement with the main implication that if a firm is included in the sorting procedures at the end of June a given year, it is included in all test portfolios and in all four factor models resulting in more comparable results across the models

5.5.4 Test Portfolios – The Dependent Variables

To test our hypotheses we use the factor models to explain the returns of various test portfolios, in which we group stocks based on some given empirical characteristic. Even though forming portfolios may change the randomness of the original data set, the portfolio formation approach is widely accepted in financial research. The main reason is that the portfolio approach has many advantages. By grouping individual stocks into portfolios, the precision with which the alphas and betas are estimated increases since the residual variances are reduced (Shanken, 1996). Also, by allowing portfolio compositions to change over time, the portfolio approach enables longer time-series than the single stock approach as stocks inevitably are listed and delisted at different points in time. Furthermore, the betas of individual stocks change considerably over time whereas portfolio betas probably are more stable and therefore easier to accurately measure (Cochrane, 2005). Nevertheless, the approach has been criticized and an example is Lo & MacKinlay (1990) who indicate that statistical tests conducted on such portfolios could generate biases in the test statistics.

When forming portfolios the idea is to sort stocks based on some characteristic believed to be related to expected returns. Desirably, the characteristic generates dispersion in average returns which is unaccounted for by the dispersion in market beta. The greater such dispersion is, the more statistical power will be obtained in subsequent regressions. These sorts do not necessarily have to be one-dimensional. For example, the benchmark double sorting procedure introduced by Fama & French (1992) is two-dimensional on size and book-to-market ratio. Despite the popularity of this sorting procedure, there is no fundamental reason for independently sorting on characteristics in more than one dimension according to Cochrane (2005). We therefore solely apply one-dimensional sorts when constructing our test portfolios, except for the Fama French benchmark double sorting for comparative reasons. Worth noting is that given a limited data set, an important trade-off arises. The more portfolios constructed, the more clearly the dispersion in average returns can be uncovered, but there is a limit. Sorting stocks into too many portfolios will diminish the advantages of the portfolio formation approach and amplify the risk of outlier firms disproportionally affecting the end result, leading to non-representative portfolios.

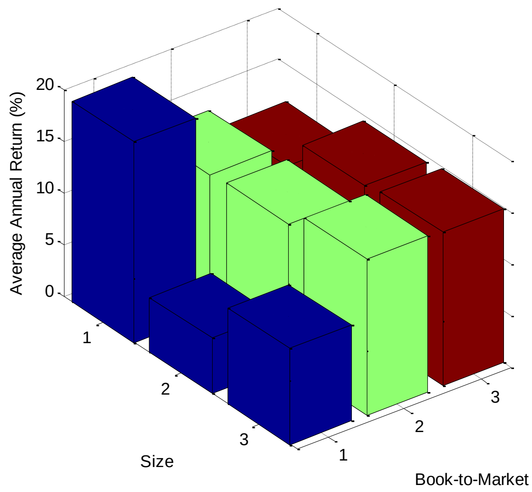
In addition to a 3x3 double sort on size and book-to-market ratio, we sort stocks into twelve portfolios based on their return-on-assets ratio and their asset growth. These sorts were chosen among other test sorts based on the reasoning explained above. Details on some of the test sorts deemed inadequate are found in Table B4. Worth mentioning is the poor relationship between average returns and pre-ranking CAPM betas (twelve to sixty months depending on data-availability) evident in the table, with an almost constant relationship. This is interesting as many U.S. studies use this sorting procedure since it usually generates a decent dispersion in average returns in line with the theoretical concept. Continuing on the topic of popular sorting procedures, we chose to refrain from using industry based test portfolios. The main reason is the trade-off mentioned earlier since an industry sort most likely would generate inadequate portfolios given the uneven Swedish industry distribution, which is documented in Table B5.

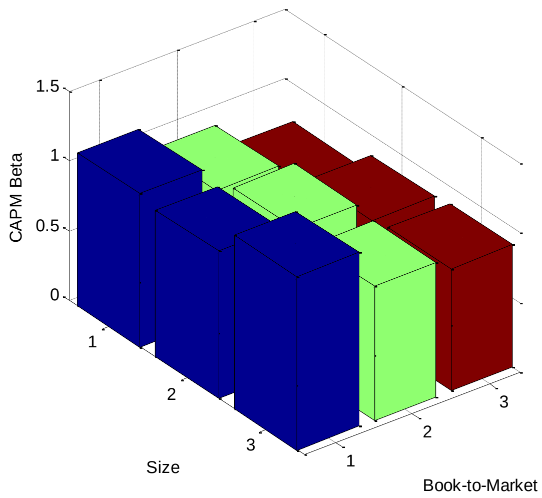
Testing the factor models on test portfolios based on distinct and different characteristics contributes to assessing their robustness. According to Cochrane (2005), this is particularly true if test portfolios are based both on characteristics affected by market prices and characteristics that are not. In our case, the double sorting on size and book-to-market ratio is directly affected by market prices (since both size and the denominator in the book-to-market ratio are derived from observations of market capitalization) whereas the remaining sorting procedures are not. Details on the sorting procedures are presented below.

Size and Book-to-Market

The procedure of creating test portfolios based on size and book-to-market ratio is, except for minor alterations, the same as the one used to create the SMB and HML factors. Instead of a 2x3 sort, each year at the end of June, we conduct two independent rankings and sort stocks into tercile portfolios based on size and book-to-market ratio. Nine portfolios, 3x3, are created at the intersection of these six portfolios. Monthly returns are calculated for the twelve consecutive months and the portfolios are thereafter rebalanced. This sorting procedure, with matrix dimensions depending on the size of the data set, is frequently used in research as it usually uncovers dispersion in average returns with average return increasing in the inverse of size, holding the book-to-market ratio constant, and in the book-to-market ratio, holding the size constant. We sort on these characteristics because it yields relatively wide observations of historical average returns and because it is a benchmark sorting procedure making our results comparable to previous studies. Descriptive statistics for the nine portfolios are found in Table B7 but average returns and market betas are presented below in Figure 1. The number three on the x-axis represents the category of portfolios including the largest firms and the number three on the y-axis represents the category of portfolios including firms with the highest book-to-market ratios (the value firms).

Figure 1 – Average annual returns (%) and CAPM betas for 3x3 portfolios, sorted on size and book-to-market ratio.





The graph illustrates that small growth firms earn the highest average returns. Although a perfectly clear pattern does not emerge, we note a tendency that value firms are related to higher average returns than growth firms (except among the smallest firms) and that average returns are not much related to size (except among the firms with the lowest book-to-market ratios). The pattern is however far from as obvious as when using U.S. data. Judging by the market beta of the nine portfolios, a significant part of the dispersion in average returns seems to be unaccounted for by the dispersion in betas, excluding the medium book-to-market category where both average returns and market betas show low dispersion. The indistinct relationship between average return and market beta shown here partially explains the poor dispersion in average returns from sorting on pre-ranking beta. Somewhat puzzling is the fact that the portfolio consisting of large growth firms shows the highest market beta and that beta is increasing in both size and market-to-book ratio. A possible explanation for this could be that many small Swedish firms are relatively illiquid and do not trade very often, which has a repressive impact on the covariance with the market. Worth noting is also that the absolute differences in betas between most portfolios are not that striking with many portfolio betas close to one, something which the figure might not display at a quick glance.

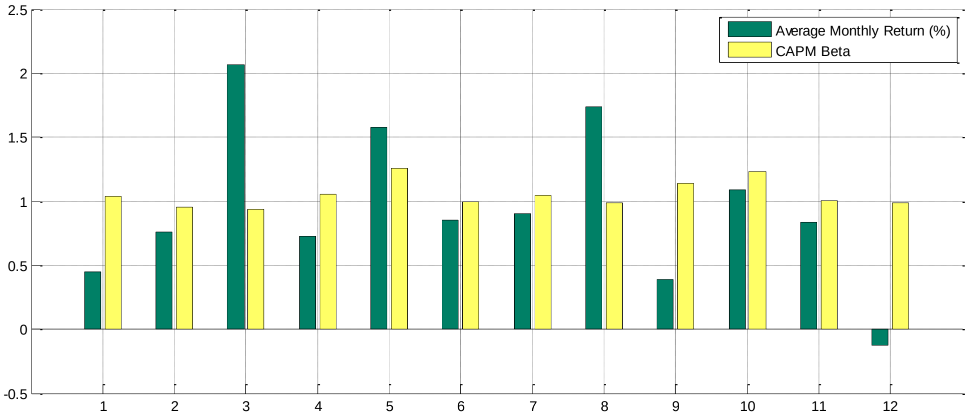
Asset Growth

Sorting on asset growth has been proven by Cooper, Gulen & Schill (2008) to reveal an anomaly with respect to the Fama French three-factor model. We are curious as to whether this holds true using Swedish data and if an investment-based factor model can reduce on the mispricing in that case. We sort stocks into twelve portfolios based on their asset growth ranking each year at the end of June. Monthly returns are thereafter computed for the twelve consecutive months. The measure of asset growth used to rank firms in June year t is defined as:

$$Asset\ Growth_{t\ (Jun)} = \frac{Total\ Assets_{t-1\ (Dec)} - Total\ Assets_{t-2\ (Dec)}}{Total\ Assets_{t-2\ (Dec)}} \tag{31}$$

Descriptive statistics for the twelve portfolios are found in Table B8 but the dispersion in average returns and in CAPM betas are illustrated in Figure 2. The portfolio consisting of firms investing the most (portfolio twelve) shows a lower average monthly return compared to the portfolio consisting of firms investing the least (portfolio one). Neither by sorting stocks on asset growth we obtain a flawless dispersion in average returns. On average portfolios consisting of low-investment firms are related to higher average returns compared to portfolios consisting of high-investment firms, although no obvious decreasing trend is present. To some extent the dispersion in average returns is accounted for by the dispersion in market betas. However, for some portfolios there is definitely more to the average return than the market beta and in one case (portfolio twelve) the two variables seem to be unrelated. Noteworthy is that the CAPM betas are fairly stable across the twelve portfolios with almost every portfolio having a beta close to one.

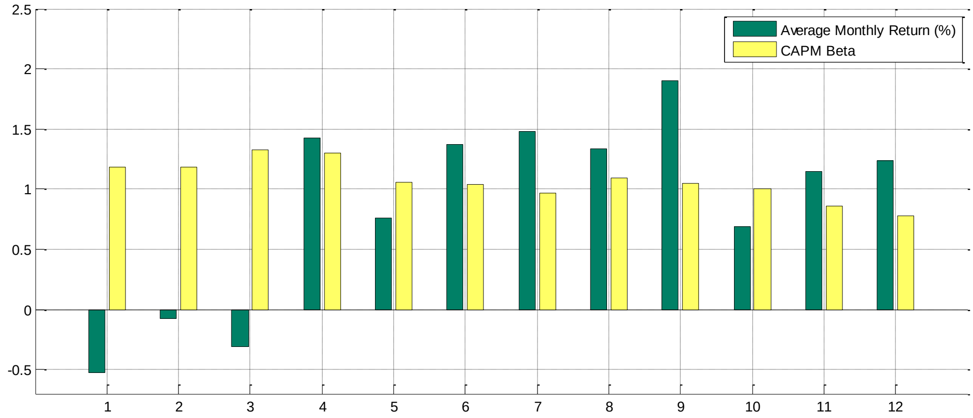
Figure 2 – Average monthly returns (%) and CAPM betas for 12 portfolios sorted on asset growth.



Return-on-Assets

Finally we also sort stocks on their return-on-assets ratio to include one additional set of test portfolios based on a characteristic unrelated to the market price. One of the factors in our slightly modified version of the alternative three-factor model is derived from the return-on-assets ratio. We therefore test all the asset pricing models on portfolios based on the same characteristic to study if, and in that case how, the investment-based factor model outperforms. We form twelve portfolios based on their R/A ratio (same measure as we use when constructing the ROA factor) each year at the end of June. Monthly returns are subsequently computed for the twelve consecutive months. The dispersion in average returns and CAPM betas are illustrated in Figure 3 and supplementary descriptive statistics are found in Table B9. Portfolios made up of firms yielding low return on assets are related to considerably lower returns than portfolios made up of firms yielding high return on assets. Although no persistent increasing trend is present here either, the pattern is more obvious than when sorting on asset growth. The CAPM betas are also in this case quite stable across the portfolios, and consequently do not account for the dispersion in average returns. Looking at the two extremes, the first and third portfolio, they earn sizable negative returns despite having the third largest and the largest CAPM beta respectively.

Figure 3 – Average monthly returns (%) and CAPM betas for 12 portfolios sorted on return-on-assets ratio.



5.5.5 Issues Related to the Portfolio Construction Procedure

Following Fama & French (1992), we make sure accounting information is known before the stock returns it is used to explain. This is done by matching the stock returns between July year t and June year $t+1$ with the accounting data for the fiscal year ending in $t-1$ and $t-2$. A drawback is that this only holds true for firms with December to May as their fiscal yearend. Only ten firms (two percent) in our data set have a different fiscal yearend, consequently we regard this as less of an issue.

As our data set contains delisted firms a technical issue arises when a firm is delisted. This issue relates to the portfolio compositions after the firm has been delisted and up until the consecutive end of June. Following Carhart (1997), if a firm is delisted during the course of the year, we include it in the factors and test portfolios up until it disappears and thereafter the portfolios are readjusted appropriately. For example, if a firm is delisted in November year t, returns for July year t to October year t are calculated as usual for the portfolios based on the rankings at the end of June year t. The returns for November year t to June year $t+1$ on the other hand are calculated for portfolios based on rankings at the end of June year t without including the delisted firm.

5.6 Factor Redundancy Test

After having run the horse race between the various asset pricing models, a closer look at the model factors and their potential relative redundancy is informative. In general, to test whether or not a certain factor, X_t, is redundant with respect to a given set of factors, Y_t and Z_t, we run a time-series regression with X_t as the dependent variable and Y_t and Z_t as the independent variables. If the regression intercept turns out to be statistically insignificant, the factor X_t is deemed redundant and can theoretically be dropped from a factor model including all three variables. An example of this is if X_t can be written as a linear combination of Y_t and Z_t, in such case Y_t and Z_t price anything that X_t prices. On the other hand, if the intercept turns out to be significant this is interpreted as X_t having pricing ability that cannot be obtained using only Y_t and Z_t. Running this type of time-series regressions also has the advantage of detecting indications of multicollinearity. According to Wooldridge (2008), multicollinearity arises for estimating factor loadings when R-squared in this context is close, but not equal, to one. An example of when this is the case is if X_t almost can be expressed as a linear combination of Y_t and Z_t.

More specifically in our case we are interested in the intra-model factor relationships of the investment-based model and its factors' contribution to the overall pricing ability. To capture a bigger part of the picture in our data set we also test the benchmark models for redundant factors. To test this we primarily run the following time-series regression equations:

$$INV_t = \alpha_{INV} + \beta_M R^e_{Mt} + \varepsilon_t \tag{32}$$

$$ROA_t = \alpha_{ROA} + \beta_M R^e_{Mt} + \varepsilon_t \tag{33}$$

$$ROA_t = \alpha_{ROA} + \beta_M R^e_{Mt} + \beta_{INV} INV_t + \varepsilon_t \tag{34}$$

$$SMB_t = \alpha_{SMB} + \beta_M R^e_{Mt} + \varepsilon_t \tag{35}$$

$$HML_t = \alpha_{HML} + \beta_M R^e_{Mt} + \beta_{SMB} SMB_t + \varepsilon_t \tag{36}$$

$$PR1YR_t = \alpha_{PR1YR} + \beta_M R^e_{Mt} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t \tag{37}$$

$$INV_t = \alpha_{INV} + \beta_M R^e_{Mt} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{PR1YR} PR1YR_t + \varepsilon_t \tag{38}$$

$$ROA_t = \alpha_{ROA} + \beta_M R^e_{Mt} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{PR1YR} PR1YR_t + \varepsilon_t \tag{39}$$

where t = 1, 2, …, 259 months. Equations (32), (33) and (34) examine the redundancy of factors in our slightly modified alternative three-factor model. Equations (35), (36) and (37) do the same for the Fama French three-factor model and the Carhart four-factor model. Lastly, equation (38) and (39) investigate whether or not the INV and ROA factors are redundant with respect to the Carhart four-factor model.

5.7 The Gibbons, Ross & Shanken F-Test

The standard absolute pricing procedure for evaluating this type of asset pricing models is by comparing their level of mispricing, measured as the number of regression intercepts statistically different from zero. In general, by running a standard time-series regression and running a t-test on the intercept, as described above, we can determine whether or not a pricing error is at hand. In our case we do this for all test portfolios, i.e. each portfolio within each test portfolio sorting procedure. This implies that when studying the intercepts of all portfolios in a certain sorting procedure, we can conclude whether or not the intercepts individually are statistically different from zero. A shortcoming of this way of testing the mispricing is that it does not account for the covariance between test portfolios and is dependent on how the portfolios are formed. To handle this issue we perform a complementary test of the mispricing using the Gibbons, Ross & Shanken's ("GRS") test statistic (refer to Equation A3 in the appendix for details). The GRS-test makes use of the F-distribution and determines if all intercepts jointly are equal to zero and the result is independent of the portfolio formation (Gibbons, Ross & Shanken, 1989). Also here we use the 5% significance level and a model is therefore rejected if the p-value of its test statistic is below 0.05.

6 Empirical Findings and Discussion of Results

6.1 Summary Statistics for the Model Factor Portfolios

The factors included in our slightly modified alternative three-factor (within this section "A3F") model together earn higher average returns[3] than the factor(s) in the CAPM, the Fama French three-factor (within this section "FF3F") model and the Carhart four-factor (within this section "C4F") model. As can be seen in Table B6 all factors earn positive average returns, except for the SML factor coming in marginally negative. The ROA factor earns the highest return, on average 1.08%, which is three times the market factor return equaling 0.36% on average. The t-test statistics show that the null hypothesis, i.e. that the mean is equal to zero, cannot be rejected at the 5% significance level for any of the factors. However, the ROA and the INV factor show the highest p-values. Worth noting is that the variance in returns is rather high for the factors, with the momentum factor sticking out as an extreme. Except for the market factor, all factors are zero-cost portfolios both long and short in stocks which ought to ease the observed portfolio variances.

As for correlations, the added factors in the A3F model show low correlations with the market factor but are notably correlated (-0.46) with one another. This is in contrast to the descriptive statistics presented by Chen et al. (2010) where this correlation is close to zero. Most likely this is related to the method used for constructing the ROA factor and more specifically the rate of portfolio rebalancing.

[3] When discussing returns within this section, we exclusively refer to monthly excess returns.

All added factors in the C4F model, including the Fama French factors, show low correlation with the market factor. In a successful construction of the Fama French factors, controlling for book-to-market ratio when creating the SMB factor and controlling for size when constructing the HML factor, the correlation between SMB and HML is expected to be close to zero. This is also the case for our factors as we find this correlation to be 0.002.

Previous studies on Swedish data have all shown an average market excess return of about 0.3% but with differing average returns for SMB, HML and the momentum factor. Bergström & Rustam (2010) find values for these three factors of -0.04%, -0.09% and -0.27% and Poutiainen & Zytomierski (2010) -0.31%, -0.27% and -0.19% respectively. Emtemark & Liu (2009), although studying mutual fund performance also calculate the same factors and come up with -0.25%, -0.23% and 1.22%. Hence, the findings in previous research are mixed, as are our results, and the only observation we find that none of the others have documented is the positive average return of the HML factor. Differences in the data set used will most likely affect these numbers and although it should not be the case, a possible reason could also be the exact method employed when calculating the figures. For a comparison of the correlation coefficients, please refer to the specific studies.

Except for the SMB factor, the factors in the FF3F model and the C4F model show relatively high mean returns, high levels of variance and low intra-model correlation coefficients. This implies that the models, and especially the C4F model, have potential to do a good job explaining both the cross-section of average returns and the variation in returns. As for the sizable positive average returns for the factors in the A3F model, they indicate that the model satisfyingly could explain a considerable part of the cross-section of average returns. Possibly the model could also explain a fair part of the variation in returns given the high variance of the factors, although this would be more likely if the INV and ROA factors did not show such a high correlation coefficient. The high level of intra-model correlation instead indicates a certain risk of multicollinearity.

6.2 Model Performance

We now turn to evaluating our slightly adjusted three-factor model relative to the already acknowledged asset pricing models using our test portfolios. This section primarily addresses our first hypothesis but also the second and third to a certain degree. Test results are presented in Table B7 - B9, one for each sorting procedure. The pricing ability is also graphically illustrated in Figure B1 - B3. Throughout this section, all general evaluations are based on the original number of test portfolios within each sorting procedure (nine, twelve and twelve). Therefore, the high minus low (H-L) portfolios included in the tables are not intended if not explicitly stated.

6.2.1 Size and Book-to-Market Portfolios

The small growth portfolio earns the highest return, on average 1.15%, but is also associated with the highest volatility. The portfolio outperforms as it shows the highest significant alpha (on average 1.11%) in all models but the CAPM. Apart from amongst the smallest firms, value firms tend to earn higher returns than growth firms as the H-L portfolio in the medium and large size groups on average earns a return of 0.76% and 0.46% per month respectively.

The average absolute intercept in the A3F model is 0.49%, equivalent to 5.88% on a yearly basis, and is economically large compared to the CAPM's 0.39%, the FF3F's 0.32% and the C4F's 0.36% indicating relative model underperformance. An illustration of this can be seen in Figure B1 which shows model predictions plotted against the average realized returns. The difference between the predicted return and the realized return is exactly equal to the estimated intercept. Since it theoretically should be a 1:1 relationship between predicted and realized returns in a perfectly specified model, all plotted values should lie along the forty-five degree line in such a case. Hence, in the graphs, the intercepts are equal to the observations' deviation from the plotted line. By comparing the four graphs in Figure B1, the deviations from the line are clearly larger for the A3F model. Also by studying the number of significant intercepts, the A3F model performs badly. Three alphas are statistically different from zero which can be compared to only one significant pricing error in the CAPM, the FF3F model and the C4F model respectively. In general however, the pricing ability is relatively good, a fact supported by the GRS-test which rejects none of the four models. In the GRS-test, the A3F model has a comparably lower p-value. This is consistent with the findings from the t-tests regarding the individual alpha significance.

When it comes to the factor loadings in the A3F model, all test portfolios load significantly on the market factor and insignificantly on the INV factor and two thirds of the portfolios have a significant ROA factor loading. The portfolios' INV betas are both statistically and economically small with an average absolute beta of 0.06 and on average within 0.70 standard errors from zero. Another observation is that many ROA factor loadings are negative making the model results seem somewhat ambiguous in light of the high positive mean value of the ROA factor. Double sorting on the same characteristics Chen et al. (2010) however find similar results. Furthermore, not only are all market factor betas significant, they are also substantially larger than the other factor loadings in absolute terms. The main impression is that the market beta seems to explain a good part of the cross-section of average returns, except among small firms, and that the two additional factors have only limited explanatory power. Turning to the FF3F model, all but two factor loadings are significant and there is a clear pattern in the factor loadings. The market beta is close to one for all portfolios. Within each book-to-market category the SMB factor loading is decreasing monotonically in size and within each size category the HML factor loading is increasing monotonically in book-to-market ratio. This indicates co-movement among small firms and firms with high book-to-market ratio. Although the market factor by itself performs very well, adding the SMB and HML factors slightly reduce on the mispricing judging by the average intercept and the precision with which these are estimated. Augmenting the Fama French equation with a momentum factor has a marginally negative effect on the pricing ability.

Regarding the variance in average returns, the values of R-squared is almost exclusionary increasing in size across the book-to-market categories for all factor models. This means that the residual sum of squares, the amount of unexplained variance, is relatively larger in portfolios consisting of small firms. This appears reasonable as returns for small stocks are more volatile and more often associated with higher idiosyncratic volatility. As for the pricing ability in terms of explaining the variation in returns the general picture stays the same. The average R-squared is 0.62, 0.58, 0.77 and 0.77 for the A3F model, the CAPM, the FF3F model and the C4F model respectively.

The A3F does not show a superior pricing ability for portfolios double sorted on size and book-to-market ratio. Instead it is the benchmark models that prevail when forming test portfolios according to this traditional procedure.

6.2.2 Asset Growth Portfolios

In the set of test portfolios sorted on asset growth, the third portfolio consisting of firms with comparatively low asset growth but not the lowest, shows an average return of 1.60% per month and is associated with a relatively low volatility. This portfolio outperforms the other portfolios as it has the highest significant alpha in all four models. The H-L portfolio earns a negative return of -0.57% per month showing that the portfolio of firms with the highest levels of investments earns a lower return than a portfolio consisting of firms with the lowest levels of investments.

The A3F model is unable to price two portfolios and the same number of significant intercepts is reported for the all of the benchmark models. All models fail in explaining the return of portfolio three and portfolio eight, being the two portfolios with the highest average returns. Thus, considering the number of pricing errors, the four models perform equally well and when taking a closer look at the absolute values of the intercepts and the t-test statistics the results are the same. The average absolute intercept in the A3F model, the CAPM, the FF3F model and the C4F model are 0.43%, 0.43%, 0.42% and 0.40% respectively. The corresponding values for the t-test statistic are 0.94, 1.02, 1.04 and 0.98. Figure B2 illustrates the predicted excess returns versus the average realized returns. By looking at the graphs it is hard to see that the average absolute alpha is equally large in the CAPM and the A3F model. What can be noted however is that the plotted observations lie closer to the forty-five degree line in the FF3F model compared to in the CAPM and in the C4F model compared to the FF3F model. This is consistent with the C4F model showing the smallest average absolute intercept. When putting the size of the intercepts in relation to the precision with which they are estimated, the models perform about equally well. On the contrary, when evaluating whether or not the intercepts are jointly equal to zero the story is different. All models are rejected by the GRS-test implying that the way of forming portfolios could have affected the models' performance when it comes to the number of individually significant alphas. Though far from failing to be rejected by the GRS-test, the A3F model shows a higher p-value compared to its opponents.

Also when sorting stocks on asset growth the market factor loadings are positive and highly significant for all test portfolios using the A3F model. For six out of twelve test portfolios significant INV betas are reported and four portfolios show significant ROA betas. INV betas decrease with the level of asset growth implying some extent of co-movement among low-investment firms as portfolios consisting of firms with low levels of asset growth load more on the INV factor. The H-L portfolio is also observed having a significant INV beta of -0.4. The A4F model primarily gets its explanatory power from the market factor although assisted by the INV factor. Within all of the benchmark models the test portfolios also show positive and highly significant loadings on the market factor. In addition to this, the HML betas in both the FF3F model and in the C4F model are negative for portfolios consisting of firms with high levels of asset growth. This is consistent with the growth-investment similarity between the HML and INV factors pointed out by Chen et al. (2010) where they emphasize that growth firms are characterized by higher levels of investments compared to value firms. In our data we observe negative HML factor loadings both for portfolios made up of growth firms in the previous sorting procedure and for portfolios made up of firms with high levels of asset growth in this sorting procedure. Finally, in the C4F model only two momentum betas are significant and the inclusion of the PR1YR factor is contributing little to explaining average returns.

The A3F and C4F models are marginally more efficient when it comes to explaining the variation in returns both having an average R-squared of 0.55 which can be compared to 0.50 for the CAPM and 0.53 for the FF3F model. As can be seen, none of the models show a high average R-squared. Instead, the R-squared values are both low and roughly equal, therefore the APT framework cannot distinguish any further differences between the models' pricing ability.

The A3F model does not improve on the mispricing for portfolios sorted on asset growth. Furthermore, if asset growth constitutes an anomaly with respect to the benchmark asset pricing models is hard to say as the two tests for alpha significance show contradicting results. In any case, a large share of the explanatory power can be attributed to the market factor, while noting that also the HML and INV factors add pieces to the puzzle.

6.2.3 Return-on-Assets Portfolios

Grouping stocks into portfolios based on their recent return-on-assets ratio reveals that portfolios consisting of firms with low return-on-assets ratios are associated with lower average returns as previously discussed. In addition to being the sorting procedure uncovering the best dispersion in average returns across the portfolios, what also is observed is that the portfolios earning the lowest average returns show higher levels of variance. The H-L portfolio earns an average return of 1.77% per month with an ordinary level of volatility. In the context of the asset pricing models, this portfolio substantially outperforms the rest of the portfolios by showing the highest significant alpha in three out of four models (on average 1.65%). The only model that can price the H-L portfolio is the A3F model as it estimates an insignificant intercept.

The number of individually significant alphas in the A3F model is two. In the CAPM, three pricing errors are observed and in the FF3F model and the C4F model the number is four and two respectively. The outperformance of the A3F model is confirmed when studying the size of the model's average absolute intercept (0.53%) and comparing it to the CAPM, the FF3F model and the C4F model (0.66%, 0.62% and 0.57% correspondingly). This is illustrated in Figure B3 where the observations lie closer to the plotted forty-five degree line when comparing the A3F model to the benchmark models. The A3F model also produces a much wider dispersion in predicted excess returns compared to its opponents. Moreover, the theme with A3F's satisfying pricing ability continues to hold true when comparing the average absolute t-test statistics. This value for the A3F model comes in at 1.29 compared to 1.51, 1.49 and 1.38 for the models in the same order as above. This implies that the precision with which the intercepts in the A3F model has been estimated, on average, is lower compared to the other models and that it is relatively less likely that they are different from zero. The p-values from the GRS-test finally confirms the pattern observed when comparing the number of individually significant alphas. Even though the null hypothesis is rejected for all models the p-value, in relative terms, is much higher for the A3F model (1.06% compared to 0.07%, 0.02% and 0.04%).

Again, all the test portfolios' loadings on the market factor are positive, significant and close to one (the average deviation from one is only 0.08) but only one portfolio loads significantly on the INV factor. When studying the ROA factor loadings an interesting observation is made. Only the betas for the first, second and third test portfolio are statistically significant, but they are all markedly negative and significant. This is interesting as these portfolios are the only portfolios earning sizeable negative average returns. Though not all significant, we also note that the ROA betas in general are increasing in the return-on-assets ratio indicating a certain degree of co-movement of stocks with high return-on-assets ratio. The H-L portfolio is well explained by the A3F model, with an insignificant alpha, a market beta of -0.08 (t = -0.63) indicating market neutrality albeit insignificant, an INV beta of -0.38 (t = -1.84) and a ROA beta of 0.91, which is more than 5.1 standard errors from zero. Overall, the model's explanatory power derives from the ROA factor combined with the market factor. The ROA factor seems to be particularly efficient in explaining average returns for portfolios made up of firms earning a low return on their assets. Within the benchmark models, the market factor continues to play an important role also when using this set of test portfolios as all market factor loadings are highly significant. Regarding the market beta, the average absolute deviation from one across the test portfolios is the highest for the CAPM (0.14) and decreases with the number of factors included in a model (0.12 for the FF3F model and 0.09 for the C4F model). As the market factor is somewhat correlated with the SMB, HML and PR1YR factors this implies that the FF3F and C4F models, being multifactor models, assign some of what in the CAPM appears to be a movement with the market factor as movements with the added factors. In the FF3F model, three SMB betas and five HML betas are significant with the only somewhat recognizable pattern that firms with low levels of return-on-assets load more on the SMB factor, hypothetically related to differences in profitability between small and large firms. The corresponding numbers of significant betas in the C4F model are three and five accompanied with four significant momentum factor loadings and also here is the same SMB loading pattern identified. Adding the momentum factor seems to improve on the explanatory power, which is in line with the results found when studying the significance of alpha.

Given the beta patterns outlined above, their contribution to the models' capacity to explain the variation in stock returns is documented by the R-squared values. Again, the variation is best explained by the A3F model and the C4F model with average R-squared values of 0.58 to be compared with 0.51 for the CAPM and 0.56 for the FF3F model. These values consolidate the results from the absolute pricing analysis, even if it is at the margin.

The A3F model reduces on the mispricing relative to all benchmark models, an outcome primarily channeled through the ROA factor. As for the benchmark models, both adding the Fama French factors to the CAPM and Carhart's momentum factor the Fama French setup improves on the mispricing as the pricing ability here is observed to increase monotonically with the number of included factors.

6.3 General Observations Regarding the Models' Performance

Across all portfolio sorts and within all factor models, the market factor demonstrates a high explanatory power. One possible reason for this could be the use of a proxy for the market factor. However, we find in untabulated results that these findings are robust to the choice of basis for the market factor. The pattern remains the same when we construct the market factor ourselves by using all stocks included in our data set, in line with the procedure used by Fama & French (1993).

Furthermore, an anticipated observation with respect to the models' ability to explain variation in returns is noted. A given regression equation's ability to fit the data cannot decrease by adding additional factors. Therefore it is only natural that we observe that the value of R-squared increases or remains the same for the A3F model and the FF3F model relative to the CAPM and for the C4F model with respect to the FF3F model within each set of test portfolios.

As previously noted, there is a substantial cross-correlation coefficient apparent within the A3F model. This concerns the INV and ROA factors and even though the absolute value of the correlation coefficient is not very close to one, there could still potentially be some issues related to multicollinearity. Although it does not affect the model's pricing ability if multicollinearity is present, the interpretation of the factor loadings naturally becomes confusing as these can change unreliably across test portfolios within the same sorting procedure. This stems from a strong linear relationship between the factors and as a result we obtain information about the pricing ability of the model as a whole without being able to distinguish the factors' individual contribution or whether or not a factor is redundant (Wooldridge, 2008). In the next section we take a closer look at potential intra-model factor redundancy and whether or not we should worry about multicollinearity.

6.4 Factor Redundancy

By running the time-series regression equations (32) - (39), this section primarily addresses our second and third hypothesis but also sheds some light over the results obtained in *6.2 Model Performance*. The results from these regressions and some supplementary regressions not explicitly outlined are found in Table B10.

Beginning with the A3F model, the estimated intercept in regression equation (32) is insignificant suggesting that the INV factor is redundant with respect to the market factor. In other words, the market factor absorbs the explanatory power of the INV factor. On the other hand, when we regress the ROA factor on the market factor using equation (33) we find a significant alpha signaling that the ROA factor is not redundant with respect to the market factor. Hence, the market factor cannot price everything that the ROA factor can. We also obtain a significant alpha when running equation (34) implying that the ROA factor bears a pricing ability that cannot be obtained even by combining the market and INV factors. The interpretation of these findings suggests that the INV factor is not a necessity for the A3F model.

As for the benchmark models, the SMB factor is redundant relative to the market factor, judging by the insignificant alpha reported for equation (35). Insignificant alphas are also obtained when running regression equations (36) and (37) suggesting that the HML factor is redundant with respect to the combination of the market and SMB factors and that the PR1YR factor is redundant with respect to the FF3F model. The HML factor and the PR1YR factor also prove redundant with respect to only the market factor.

We continue by running the regression equations (38) and (39) and find that INV is redundant relative the C4F model (as expected) whereas the ROA factor is not as it shows a significant alpha of 1.10% (t = 3.18). Thus, the ROA factor has some pricing ability that cannot be obtained even by using a combination of the market, HML, SMB and PR1YR factors.

Finally, when studying the R-squared values in Panel A of Table B10, none of them are even close to one. This observation leads us to regard multicollinearity as less of an issue for the employed factor models and we are therefore more confident in relying on our results obtained in the previous section.

6.5 Hypotheses Evaluation

Below we evaluate our hypotheses in light of our empirical findings. The key results obtained are summarized in Figure 4.

Figure 4 – Key empirical findings.

Size and Book-to-Market Portfolios	**Avg. absolute alpha (%)**	**Nr. of significant alphas**	**Rejected by the GRS-test**
The A3F model	0.49	3/9	No
The CAPM	0.39	1/9	No
The FF3F model*	0.32	1/9	No
The C4F model	0.36	1/9	No
Asset Growth Portfolios	**Avg. absolute alpha (%)**	**Nr. of significant alphas**	
The A3F model	0.43	2/12	Yes
The CAPM	0.43	2/12	Yes
The FF3F model	0.42	2/12	Yes
The C4F model*	0.40	2/12	Yes
Return-on-Assets Portfolios	**Avg. absolute alpha (%)**	**Nr. of significant alphas**	
The A3F model*	0.53	2/12	Yes
The CAPM	0.66	3/12	Yes
The FF3F model	0.62	4/12	Yes
The C4F model	0.57	2/12	Yes

*) Overall best performing model within the specific test portfolio sorting procedure.

Factor Redundancy	**Factor redundant to these factors/combination of factors**
INV	Market - Market, SMB, HML and PR1YR
ROA	*Factor not redundant*
SMB	Market
HML	Market - Market and SMB
PR1YR	Market - Market, SMB and HML

6.5.1 Hypothesis 1

A multifactor asset pricing model including two independent variables based on the firm characteristics investments-to-assets ratio and return-on-assets ratio, in addition to the market factor, can better explain the cross-section of Swedish average stock returns compared to the CAPM, the Fama French three-factor model and the Carhart four-factor model.

Using absolute pricing, by studying the number of individually significant intercepts and the probability values obtained when testing the intercepts for joint significant for all models and test portfolios, we find that the results relating to our first hypothesis are not unambiguous. Neither by using relative pricing and the APT framework we obtain results pointing in one single direction. First of all, the market factor is able to price most of the test portfolios remarkably well. When augmenting the CAPM with the INV and ROA factors the mispricing: is reduced for test portfolios based on the return-on-assets measure, is equivalent to the benchmark models for test portfolios based on the asset growth measure and is higher for test portfolios double sorted on size and book-to-market ratio. Therefore we can neither clearly reject nor fail to reject our first hypothesis. Our interpretation is that none of the models we assess are sufficiently robust to explain all our test portfolios and since the A3F model has proven its high pricing ability for one of the sorting procedure its usefulness cannot be disregarded. The model should therefore be used as a complement to the existing benchmark models.

6.5.2 Hypothesis 2

An independent variable based on the firm characteristic investments-to-assets ratio demonstrates a pricing ability that is not captured by the market factor.

We show that the INV factor is redundant with respect to the market factor as no significant intercept is obtained when testing for factor redundancy using equation (32). Hence, the factor does not add explanatory power in excess of the market factor with respect to the cross-section of average stock returns in Sweden. We therefore reject our second hypothesis. From the empirical tests made using our test portfolios and the time-series regression approach there are no clear indications that the INV factor helps reduce the mispricing. The only observation we note is some explanatory power relating to the variation in stock returns when test portfolios are sorted based on the asset growth measure. As the market factor absorbs its pricing ability, the INV factor is not a necessity for the A3F model. This makes us question the current three-factor composition of the alternative investment-based factor model in the Swedish setting. Our results indicate that a two-factor model consisting of solely the market and the ROA factors could be sufficient.

6.5.3 Hypothesis 3

An independent variable based on the firm characteristic return-on-assets ratio demonstrates a pricing ability that is not captured by the market factor.

Our results from testing all four models for redundant factor(s) confirm the general observation made when applying the factor models to our test portfolios, namely that the market portfolio accounts for a major part of the explanatory power. For example, all additional factors included in the C4F model prove redundant relative to the market factor. Nevertheless, the ROA factor seems to have explanatory power to add regarding the cross-section of Swedish average returns. When estimating the intercept in equation (33) we find it to be statistically significant demonstrating the ROA factor's meaningful pricing ability which is not captured by the market factor. This is not the case for any of the other factors used in our study. We therefore fail to reject our third hypothesis. Also, even when examining the factor's pricing ability relative to the whole C4F model, the result remains the same. The high pricing capability demonstrated by the ROA factor seems to be the main reason why the A3F model shows partial outperformance relative the acknowledged benchmark models.

6.6 Proposing an Alternative Two-Factor Model

Continuing on the reasoning we made when evaluating our second hypothesis we briefly look at the pricing ability of a proposed two-factor model consisting solely of the market and the ROA factors. As can be seen in Table B11, we find that this alternative two-factor model actually improves on some of the aspects of the mispricing for test portfolios sorted on return-on-assets ratios. Compared to the A3F model, the proposed two-factor model shows the same number of significant alphas, the same average R-squared, a lower average absolute intercept (0.49% vs. 0.53%), a lower average absolute t-test statistic (1.19 vs. 1.29), but also a slightly lower p-value for the GRS-test (0.98% vs. 1.06%). On the other hand, for the other two sets of test portfolios the performance is worse than that of the A3F model, albeit only marginally. In our set-up, using an alternative investment-based factor model as a complement to existing benchmark models is most useful when trying to price portfolios sorted on return-on-assets ratio. If this is a practitioner's intention, he/she obtains an equally satisfying (if not better) result using the simplified two-factor model.

6.7 Limitations and Potential Shortcomings

6.7.1 Data Issues

There are two types of data concerns in a study like ours, the availability and quality of the data retrieved and the impact of our adjustments on the original data set. The availability and quality of data on Swedish firms is scarce compared to U.S. data. This was first and foremost noticeable as we early on realized that interim accounting data used in the original study by Chen et al. (2010) to construct the ROA factor was inaccessible. For this reason we instead based the factor on annual data, which might partly explain general differences in performance between our model and Chen et al.'s model. Furthermore accounting numbers were completely missing for some firms in our data set, and were insufficient for others. This was especially apparent further back in time. We tried to reduce this problem by also collecting data from Compustat and not solely rely on Datastream. The absence of certain data and consequently the exclusion of the related firms might have biased our results, despite being an issue somewhat beyond our control.

Related to the data-availability concerns is our study's partial survivorship bias. Before retrieving any data from the databases we identified all firms delisted at any point during our time period. Despite this effort it was apparent that the data on delisted firms was very poor in both Datastream and Compustat, making it possible to include only 191 out of the 525 delisted firms. This implies that although not suffering from an absolute survivorship bias there is in part a survivorship bias in our study which might have affected our final results.

We also did some adjustments to the original raw data set. In order to facilitate the sorts and for consistency reasons we imposed a certain data-availability requirement (see *4.2.1 Omitted Data*), which slightly decreased the number of data points. We also cleared our data set of SDRs and adjusted it for issues related to some firms' negative book value of equity. Our ambition was to only do adjustments necessary for comparative purposes within our empirical study and not to polish the data set, but it cannot be ruled out that these adjustments have impacted our results.

6.7.2 The Test Portfolios

When conducting a horse race between different linear factor models of this kind the test portfolios play an important role. Preferably, the sorting procedure using a characteristic believed to be related to the expected return should produce a perfectly nice dispersion in average returns across the test portfolios. More explicitly, a monotonically increasing/decreasing trend should preferably be apparent and related to the initial theoretical relationship. As an example, when comparing the double sorting procedure on size and book-to-market ratio the pattern is extremely clear using U.S. data whereas this is not the case in Sweden. The better such results are, in terms of dispersion in average returns, the more reliable are the end results from the statistical evaluation. As our three sorting procedures only have uncovered the overall trends in average returns across the test portfolios this aspect of our empirical results is somewhat off the ideal scenario. Although this possibly can stem from an absence of such strong patterns in Swedish stock returns data it may perhaps have affected our results.

7 Conclusion

7.1 Concluding Remarks

When evaluating the relative pricing ability of an alternative three-factor model with its roots within investment-based asset pricing we find that it shows some explanatory power in excess of already acknowledge benchmark models. Test portfolios based on return-on-assets ratio are better priced using our slightly adjusted alternative three-factor model. For other sorts, especially the popular double sorting procedure on size and book-to-market, the Fama French three-factor model and the Carhart four-factor model still prevail.

When dissecting our slightly adjusted alternative three-factor model and examining the independent factors' individual contribution to the model's overall pricing ability we find that the market factor and the ROA factor demonstrate high pricing ability while the INV factor is redundant.

As for the performance of the benchmark models our results show that they in general perform well. Since the SMB, HML and PR1YR factors all prove redundant with respect to the market factor, the main part of this performance is attributable to the market factor. This is also confirmed by the fact that the CAPM in general performs well and that no exceptional improvement of the classical model's pricing ability is shown by either the Fama French three-factor model or the Carhart four-factor model. Compared to previous master's theses, these findings are contradicting the results of Poutiainen & Zytomierski (2010), signaling that the performance of the traditional models is improved when using a more extensive and representative data set. However, the results are roughly in line with those of Bergström & Rustam (2010), but there is a discrepancy in this comparison as the length of our time-series data is almost two times theirs. Worth underlining is that these comparisons only relate to the set of test portfolios double sorted on size and book-to-market ratio, as this is the only test portfolio sorting procedure the studies have in common. In any case, one possible explanation could be that the use of the OMX AFGX as a proxy for the market return is more representative when the data set only suffers from a partial survivorship bias.

Following the results concluding redundancy of the INV factor we propose a two-factor model, where the CAPM is augmented with only the ROA factor, and briefly look at this model's relative performance. Compared to our slightly adjusted alternative three-factor model the more basic two-factor model performs equally well, if not better, for test portfolios sorted on return-on-assets ratio but worse for the other test portfolios. The aggregate picture of our results shows that no single model is robust enough to efficiently price all test portfolios. An investment-based factor model has, to some extent, a pricing ability which is not captured by the traditional models. In our case, it makes most sense to use such a model when pricing test portfolios sorted on return-on-assets ratio. We show that if this indeed is the case, someone looking for a complement to the existing benchmark models would find it sufficient to use the simplified two-factor model.

On a more general note, in this thesis we use a number of parameters, believed to be related to expected returns, to sort stocks into portfolios. When comparing the average returns for the portfolios within each sorting procedure no perfectly monotonically increasing/decreasing trend is apparent. Whether this is related to a general absence of such obvious relationships when it comes to Swedish stock return data is hard to say. We only observe that this is not the case for the characteristics we have looked at and conclude that in order to bring clarity to the matter further research within the field is necessary.

7.2 Suggestions for Further Research

Given the mixed results we obtain the pursuit of the optimal factor model continues. The problem of finding the best-performing and most robust linear asset pricing model may be attacked from multiple angles. A fundamental start would be to test the dispersion in average returns for numerous characteristics believed to be related to expected returns. Interesting would be to see if any obvious trends can be uncovered. If so, one would proceed by testing the factor models' performance using test portfolios sorted on this/these characteristic(s) to determine the investment-based asset pricing model's relative performance. One idea would be to start examining if test portfolios sorted on earnings surprises, various distress measures and short-term prior returns uncover a satisfying dispersion in average returns. Another would be to investigate if our results are robust to the choice of stock market or if the results obtained can have been affected by the nature of the data set. Other European countries would be a good place to start and especially a country where interim accounting data is well-documented.

Lastly, the relatively high pricing ability of the ROA factor combined with the wide alpha dispersion for portfolios sorted on return-on-assets ratio (shown in Figure B3) make up an interesting foundation for continued research. Having performed the analysis in the time-series dimension, one becomes curious as to what estimates in the cross-sectional dimension would look like. By conducting a Fama MacBeth two-pass cross-sectional regression it would be highly interesting to study how well the asset characteristic return-on-assets ratio describes the cross-section of average returns. Maybe even it can drive out the significance of some of the traditional characteristics?

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Appendix A: Equations

Equation A1

The Fischer (1930) model

Following the notation of Mark Rubinstein (2006), Fischer's (1930) model is given by:

- $U(C_0), U(C_1)$ is the utility of consumption at dates 0 and 1
- ρ is the rate of patience or time preference of consumption
- Ω_0 is the initial endowment of the consumption good
- X_0 is the investment, so that $C_0 = \Omega_0 - X_0$
- $f(X_0)$ is the output of production of date 1 consumption, $C_1 = f(X_0)$
- W_0 is the current wealth of the consumer, so that $W_0 = C_0 + \frac{C_1}{r}$

We assume that $U'(C) > 0$ (nonsatiation), $U''(C) < 0$ (diminishing marginal utility), $0 < \rho < 1$ (tendency to prefer current consumption over future consumption), $f'(X_0) > 0$ (more input yields more output), $f''(X_0) < 0$ and (diminishing returns to scale). The production problem for the consumer is then given by:

$$\max_{C_0,C_1} U(C_0) + \rho U(C_1) \quad s.t. C_0 = \Omega_0 - X_0 \; and \; C_1 = f(X_0)$$

Inserting the constraints, differentiating the utility function and setting the derivative equal to zero gives:

$$\frac{U'(C_0)}{\rho U'(C_1)} = f'(X_0)$$

The optimal consumption problem/exchange problem for the consumer is:

$$\max_{C_0,C_1} U(C_0) + \rho U(C_1) \quad s.t. W_0 = C_0 + \frac{C_1}{r}$$

Again, inserting the constraint, differentiating the utility function and setting the derivative equal to zero gives:

$$\frac{U'(C_0)}{\rho U'(C_1)} = r$$

This implies also that $f'(X_0) = r$. In other words, the interest rate or the equilibrium risk-free return equals the marginal rate of substitution and the marginal productivity of capital. Similarly, the optimal production problem for a value-maximizing competitive firm is given by:

$$\max_{X_0} -X_0 + \frac{f(X_0)}{r}$$

Differentiating the formula and setting it equal to zero gives that $f'(X_0) = r$, i.e. the exact same decision as the consumer found (Rubinstein, 2006). Fischer's framework implies that you can find the equilibrium interest rate from either the partial equilibrium consumption decision or the partial equilibrium production decision, as they both should provide the same answer (Zhang, 2010). So even if researchers have historically favored the consumption based approach, Fischer's (1930) model shows that the same conclusions could be drawn from the production side, and this is where the growing field of investment based asset pricing has its starting point.

Equation A2

The Liu, Whited & Zhang (2009) model

The Liu, Whited & Zhang's (2009) model that links securities returns solely to the production side following the notation of Zhang (2010):

$$r_{it+1}^{S} = \frac{(1-\tau_{t+1})\left[\alpha\frac{Y_{it+1}}{K_{it+1}}+\frac{\alpha}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right]+\tau_{t+1}\delta_{it+1}+(1-\delta_{it+1})\left[1+(1-\tau_{t+1})a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]}{\frac{\underline{1+(1-\tau_t)a\left(\frac{I_{it}}{K_{it}}\right)}}{1-w_{it}}} - w_{it}r_{it+1}^{Ba}$$

where

- r_{it+1}^{S} is the stock return for security *i* from *t* to *t+1*
- τ_{t+1} is the corporate tax rate
- α is the capital's share in output
- $\frac{Y_{it+1}}{K_{it+1}}$ is sales-to-capital
- $a > 0$ is the adjustment cost parameter
- $\frac{I_{it}}{K_{it}}$ is investment-to-capital
- δ_{it+1} is the rate of capital depreciation
- w_{it} is the market leverage ratio
- r_{it+1}^{Ba} is the corporate bond return (after-tax)

Equation A3

The GRS test statistic presented by Gibbons, Ross & Shanken (1989)

The GRS test statistic introduced by Gibbons, Ross & Shanken (1989) and used for testing the joint significance of alphas in a time-series regression based on excess returns is given by:

$$\frac{T-N-K}{N}\left(1+\bar{f}'\hat{\Sigma}_f^{-1}\bar{f}\right)^{-1}\hat{\alpha}'\hat{\Sigma}_\varepsilon^{-1}\hat{\alpha} \sim F_{N,T-N-K}$$

where

- ε are assumed to be normally distributed and i.i.d.
- T is the number of time periods (sample size)
- N is the number of test assets
- K is the number of factors
- $\bar{f}$ is the vector of sample means of the factors

$$\bar{f} = [\ \bar{f}_1 \quad \bar{f}_2 \quad \dots \quad \bar{f}_K\ ]'$$

- $\bar{\alpha}$ is the vector of estimated intercepts from the N time-series regressions

$$\hat{\alpha} = [\ \hat{\alpha}_1 \quad \hat{\alpha}_2 \quad \dots \quad \hat{\alpha}_N\ ]'$$

- $\hat{\Sigma}_f$ is the estimated factor covariance matrix

$$\hat{\Sigma}_f = \frac{1}{T}\sum_{t=1}^{T}(f_t-\bar{f})(f_t-\bar{f})'$$

- $\hat{\Sigma}_\varepsilon$ is the estimated covariance matrix of the residuals in the N time-series regressions

$$\hat{\Sigma}_\varepsilon = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$$

where $\hat{\varepsilon}_t$ is the N x 1 vector of residuals for each t

$$\hat{\varepsilon}_t = \ [\ \hat{\varepsilon}_t^1 \quad \hat{\varepsilon}_t^2 \quad \dots \quad \hat{\varepsilon}_t^N\ ]'$$

with

$$\hat{\varepsilon}_t^i = R_t^{ei} - (\hat{\alpha}_i + \hat{\beta}_{i,f^1}f_t^1 + \hat{\beta}_{i,f^2}f_t^2 + \cdots)$$

Appendix B: Figures and Tables

Table B1

Datastream Mnemonics and Compustat Items

The table shows the Datastream mnemonics and Compustat items used to collect the market data and accounting data from the databases.

Table B1 Datastream mnemonics and Compustat items

	Source	
	DS Mnemonic	**COMPUSTAT item**
- Market data (monthly)		
Total Return Index	RI	-
Market Capitalization	WC08001	-
- Accounting data (yearly)		
Book value of equity	WC03501	CEQ
Net income before extraodinary items	WC01551	IB
Total PPE (Gross)	WC02301	PPEGT
Total Assets	WC02999	AT
Total Inventories	WC02101	INVT

Table B2

Firms Included in the Final Data Set

The table shows firms included in the final data set. A company name with the superscript one (1) indicates that the firm is active. A company name with the superscript two (2) indicates that the firms is delisted. Company names occurring more than once are the results of various corporate actions (e.g. mergers or spin-offs) or simply delisted firms that later on are relisted.

Table B2 Firms included in the final data set

1	AARHUSKARLSHAMN AB [1]	22	ALTHIN MEDICAL AF [2]	43	BALLINGSLOV INTL.AB [2]
2	AB LINJEBUSS [2]	23	ANDERS DIOS [2]	44	BE GROUP AB [1]
3	AB SEGERSTROM & SVENS. [2]	24	ANOTO GROUP AB [1]	45	BEIJER ALMA AB [1]
4	ACADEMEDIA AB [2]	25	ARGONAUT A [2]	46	BEIJER ELECTRONICS AB [1]
5	ACANDO AB [1]	26	ARITMOS [2]	47	BERGS TIMBER AB [1]
6	ACAP INVEST AB [1]	27	ARTIMPLANT AB [1]	48	BETSSON AB [1]
7	A-COM AB [1]	28	ASG AB [2]	49	BIACORE INTERNATIONAL AB [2]
8	ACRIMO B [2]	29	ASPIRO AB [1]	50	BILIA AB [1]
9	ACTIVE BIOTECH AB [1]	30	ASSA ABLOY AB [1]	51	BILLERUD AB [1]
10	ADDNODE AB [1]	31	ASSIDOMAN AB [2]	52	BILSPEDITION [2]
11	ADDTECH AB [1]	32	ASTRA AB [2]	53	BIOGAIA AB [1]
12	AEROCRINE AB [1]	33	ATLAS COPCO AB [1]	54	BIOINVENT INTL.AB [1]
13	AF AB [1]	34	ATLE [2]	55	BIOLIN SCIENTIFIC AB [1]
14	AFFARSSTRATEGERNA AB [2]	35	ATRIUM LJUNGBERG AB [1]	56	BIOPHAUSIA AB [1]
15	AGA AB [2]	36	AU SYSTEM [2]	57	BIORA AB [2]
16	ALFA LAVAL AB [1]	37	AUDIODEV AB [2]	58	BIOTAGE AB [1]
17	ALFA LAVAL AB [2]	38	AVESTA SHEFFIELD AB [2]	59	BJORN BORG AB [1]
18	ALFASKOP AB [2]	39	AXFOOD AB [1]	60	BOLIDEN AB [1]
19	ALL CARDS SER.CENTER AB [2]	40	AXIS AB [1]	61	BONG LJUNGDAHL AB [1]
20	ALLGON [2]	41	B&B TOOLS AB [1]	62	BORAS WAFVERI AB [2]
21	ALLIANCE OIL CO.LTD. [1]	42	BAHCO [2]	63	BOSS MEDIA AB [2]

64 BRINOVA FASTIGHETER AB [1]
65 BRIO AB [2]
66 BROSTROMS REDERI [2]
67 BT INDUSTRIES AB [2]
68 BTS GROUP AB [1]
69 BULTEN [2]
70 BURE EQUITY AB [1]
71 CAPIO AB [2]
72 CARDO AB [1]
73 CASHGUARD AB [2]
74 CASTELLUM AB [1]
75 CATELLA 'A' [2]
76 CATENA AB [1]
77 CELL NETWORK AB [2]
78 CELLAVISION AB [1]
79 CELSIUS AB [2]
80 CELTICA FASTIGHETS AB [2]
81 CISION AB [1]
82 CLAS OHLSON AB [1]
83 CLOETTA AB [1]
84 CONCORDIA MARITIME AB [1]
85 CONNECTA AB [1]
86 CONSILIUM AB [1]
87 COREM PROPERTY GROUP AB [1]
88 CTT SYSTEMS AB [1]
89 CUSTOS AB [2]
90 CYBERCOM GROUP EUROPE AB [1]
91 CYNCRONA B [2]
92 DAGON AB [1]
93 DAHL INTERNATIONAL AB [2]
94 DGC ONE AB [1]
95 DIAL NXT GROUP AB [2]
96 DIAMYD MEDICAL AB [1]
97 DIFFCHAMB AB [2]
98 DIGITAL VISION AB [1]
99 DIMENSION [2]
100 DIN BOSTAD SVERIGE AB [2]
101 DIOS FASTIGHETER AB [1]
102 DORO AB [1]
103 DUNI AB [1]
104 DUROC AB [1]
105 ELANDERS AB [1]
106 ELDON AB [2]
107 ELECTRA GRUPPEN AB [1]
108 ELECTROLUX AB [1]
109 ELEKTA AB [1]
110 ELEKTRONIKGRUPPEN BK AB [1]
111 ELOS AB [1]
112 ENATOR [2]
113 ENEA AB [1]
114 ENIRO AB [1]
115 ENTRA DATA AB [2]
116 ENTRACTION HOLDING AB [2]
117 EPSILON B [2]
118 ERICSSON TELEPHONE AB [1]
119 ESAB [2]
120 ESSELTE AB [2]
121 EUROPOLITAN VODAFONE AB [2]
122 EVIDENTIA AB [2]
123 EWORK SCANDINAVIA AB [1]
124 FABEGE AB [1]
125 FABEGE AB [2]
126 FABEGE AB [2]
127 FAGERHULT AB [1]
128 FAGERLID INDUSTRIER AB [2]
129 FAST PARTNER AB [1]
130 FASTIGHETS BALDER AB [1]
131 FAZER KONFEKTYR SER.AB [2]
132 FB INDUSTRI [2]
133 FEELGOOD SVENSKA AB [1]
134 FENIX OUTDOOR AB [1]
135 FINGERPRINT CARDS AB [1]
136 FINNVEDEN AB [2]
137 FOLKEBOLAGEN B [2]
138 FORCENERGY AB [2]
139 FORMPIPE SOFTWARE AB [1]
140 FORSHEDA [2]
141 FRANGO AB [2]
142 FRILUFTSBOLAGET E & S [2]
143 FRONTLINE AB [2]
144 G & L BEIJER AB [1]
145 GAMBRO AB [2]
146 GAMBRO AB [2]
147 GANT COMPANY AB [2]
148 GETINGE AB [1]
149 GEVEKO AB [1]
150 GLOBAL HEALTH PTNS.AB [1]
151 GLOCALNET AB [2]
152 GORTHON LINES AB [2]
153 GOTLAND REDERI AB [2]
154 GRANINGE AB [2]
155 GULLSPANGS KRT [2]
156 GUNNEBO AB [1]
157 GUNNEBO INDUSTRIER AB [2]
158 H&M HENNES & MAURITZ AB [1]
159 HAKON INVEST AB [1]
160 HALDEX AB [1]
161 HAVSFRUN INVESTMENT AB [1]
162 HEBA AB [1]
163 HEMTEX AB [1]
164 HEXAGON AB [1]
165 HEXAGON AB [2]
166 HEXPOL AB [1]
167 HIFAB GROUP AB [2]
168 HIQ INTERNATIONAL AB [1]
169 HL DISPLAY AB [2]
170 HMS NETWORKS AB [1]
171 HOGANAS AB [1]
172 HOLMEN AB [1]
173 HOME PROPERTIES AB [2]
174 HQ FONDER AB [2]
175 HUFVUDSTADEN AB [1]
176 HUMAN CARE H C AB [2]
177 HUMLEGARDEN AB [2]
178 HUSQVARNA AB [1]
179 IAR SYSTEMS AB [2]
180 IBS AB [2]
181 ICB SHIPPING AB [2]
182 INDL.& FINL.SYS.AB [1]
183 INDUSTRIFORVALTNINGS AB [2]
184 INDUSTRIVARDEN AB [1]
185 INDUTRADE AB [1]
186 INTELLECTA AB [1]
187 INTELLIGENT MICRO SYS.AB [2]
188 INTENTIA INTL.AB [2]
189 INTOI AB [1]
190 INTRUM JUSTITIA AB [1]
191 INVESTMENT AB KINNEVIK B [1]
192 INVESTOR AB [1]
193 IRO AB [2]
194 ITAB SHOP CONCEPT AB [1]
195 J&W JACOBSON & WIDMARK [2]
196 JC AB [2]
197 JEEVES INFO.SYSTEMS AB [1]
198 JLT MOBILE COMPUTERS AB [2]
199 JM AB [1]
200 KABE HUSVAGNAR AB [1]
201 KALMAR INDUSTRIES AB [2]
202 KAPPAHL HOLDING AB [1]
203 KARLSHAMNS AB [2]
204 KARO BIO AB [1]
205 KAROLIN INVEST [2]
206 KAROLIN MACHINE TOOL AB [2]
207 KIPLING HLDG [2]
208 KJESSLER&MANNERSTRALE [2]
209 KLIPPANS FINPAPPERSBRUK [2]
210 KLOVERN AB [1]
211 KLOVERN AB [2]
212 KNOW IT AB [1]
213 KUNGSLEDEN AB [1]
214 LABS2GROUP AB [2]
215 LAGERCRANTZ AB [1]
216 LAMMHULTS DESIGN GP.AB [1]
217 LATOUR INVESTMENT AB [1]
218 LBI INTERNATIONAL NV [2]
219 LEDSTIERNAN AB [2]
220 LGP ALLGON HOLDING AB [2]
221 LINDAB INTERNATIONAL AB [1]
222 LINDAB INTERNATIONAL AB [2]
223 LINDEX AB [2]
224 LINKMED AB [1]
225 LODET FASTIGHETS [2]
226 LOOMIS AB [1]
227 LUNDBERGFORETAGEN AB [1]
228 LUNDIN OIL AB [2]
229 LUNDIN PETROLEUM AB [1]
230 M2S SVERIGE [2]
231 MALMBERGS ELEKTRISKA AB [1]
232 MANDAMUS [2]
233 MANDATOR AB [2]
234 MARIEBERG TID.AB [2]
235 MEDA AB [1]
236 MEDICOVER HOLDING SDB SA [2]
237 MEDIVIR AB [1]
238 MEKONOMEN AB [1]
239 MICRONIC MYDATA AB [1]
240 MIDSONA AB [1]
241 MIDWAY HOLDINGS AB [1]
242 MIND [2]
243 MOBYSON AB [1]
244 MODERN TIMES GP.MTG AB [1]
245 MODUL 1 DATA AB [1]
246 MORPHIC TECHNOLOGIES AB [1]
247 MSC KONSULT AB [1]
248 MULTIQ INTERNATIONAL AB [1]
249 MUNKSJO [2]
250 MUNTERS AB [2]
251 NACKEBRO AB [2]
252 NAN RESOURCES AB [2]
253 NCC AB [1]
254 NEA NARKES ELECTRISKA AB [2]
255 NEDERMAN HOLDING AB [1]
256 NEFAB AB [2]
257 NET ENTERTAINMENT NE AB [1]
258 NET INSIGHT AB [1]
259 NETONNET AB [1]
260 NETWISE AB [2]
261 NEW WAVE GROUP AB [1]
262 NIBE INDUSTRIER AB [1]
263 NILORNGRUPPEN AB [2]
264 NISCAYAH GROUP AB [1]
265 NOBEL BIOCARE HOLDING AG [2]
266 NOBIA AB [1]
267 NOLATO AB [1]
268 NORDIC ACS.BUYOUT FD.AB [1]
269 NORDIC MINES AB [1]
270 NORDIC SER.PTNS.HDG.AB [1]
271 NORDIFAGRUPPEN AB [2]
272 NORDSM.& THULIN AB [2]
273 NORRPORTEN FTGH. AB [2]
274 NOTE AB [1]
275 NOVACAST TECHNOLOGIES AB [1]
276 NOVOTEK AB [1]
277 ODD MOLLY INTL. AB [1]
278 OEM INTERNATIONAL AB [1]
279 OPCON AB [1]
280 OPTIMAIL AB [2]
281 ORC SOFTWARE AB [1]
282 OREXO AB [1]
283 ORREFORS KOSTA BODA [2]
284 ORTIVUS AB [1]
285 PA RESOURCES AB [1]
286 PANDOX AB [2]
287 PARTNERTECH AB [1]
288 PEAB AB [1]
289 PERBIO SCIENCE [2]
290 PERGO AB [2]
291 PERSTORP AB [2]
292 PHARMACIA [2]
293 PHAROS [2]
294 PHONERA AB [1]
295 PIREN [2]
296 POOLIA AB [1]
297 PRECISE BIOMETRICS AB [1]
298 PRICER AB [1]
299 PRIFAST AB [2]
300 PROACT IT GROUP AB [1]
301 PROBI AB [1]
302 PROFFICE AB [1]
303 PROFILGRUPPEN AB [1]

304	PRONATOR [2]	338	SEMCON AB [1]	372	TELELOGIC AB [2]
305	PRONYX [2]	339	SENEA AB [2]	373	TELIASONERA AB [1]
306	PROTECT DATA AB [2]	340	SENSYS TRAFFIC AB [1]	374	TELIGENT AB [2]
307	PROVENTUS [2]	341	SIAB [2]	375	TERRA MINING AB [2]
308	Q-MED AB [1]	342	SIGMA AB [1]	376	THORSMAN [2]
309	RAYSEARCH LABS.AB [1]	343	SINTERCAST AB [1]	377	TICKET TRAVEL GROUP AB [2]
310	READSOFT AB [1]	344	SKANDITEK INDRI.FRV.AB [2]	378	TILGIN AB [2]
311	REDERI AB TRANSATLANTIC [1]	345	SKANE-GRIPEN [2]	379	TIVOX AB [2]
312	REJLERKONCERNEN AB [1]	346	SKANSKA AB [1]	380	TORNET FASTIGHETS AB [2]
313	RESCO AB [2]	347	SKF AB [1]	381	TRACTION AB [1]
314	REZIDOR HOTEL GROUP AB [1]	348	SKISTAR AB [1]	382	TRADEDOUBLER AB [1]
315	RIDDARHYTTAN RES.AB [2]	349	SKOOGS AB [2]	383	TRELLEBORG AB [1]
316	RKS AB [2]	350	SOFTRONIC AB [1]	384	TRICORONA AB [2]
317	RNB RETAIL AND BRANDS AB [1]	351	SOLITAIR KAPITAL AB [2]	385	TRIO INFO.SYSTEMS AB [2]
318	RORVIK TIMBER AB [1]	352	SONG NETWORKS HLDG. AB [2]	386	TRUSTOR AB [2]
319	ROTTNEROS AB [1]	353	SPENDRUPS BRYGGERI AB [2]	387	TURNIT AB [2]
320	SAAB AB [1]	354	SSAB AB [1]	388	TV4 AB [2]
321	SAK I AB [1]	355	STENA LINE AB [2]	389	UNIFLEX AB [1]
322	SALUS ANSVAR AB [2]	356	STORA AB [2]	390	UNITED TANKERS AB [2]
323	SAND.& STOHNE [2]	357	STRALFORS AB [2]	391	UTFORS [2]
324	SANDVIK AB [1]	358	STUDSVIK AB [1]	392	WALLENSTAM AB [1]
325	SAPA AB [2]	359	SWECO AB [1]	393	VBB GRUPPEN AB [2]
326	SARDUS AB [2]	360	SWED.ORPHAN BIOVITRUM AB [1]	394	VBG GROUP AB [1]
327	SAS AB [1]	361	SVEDALA INDUSTRIER AB [2]	395	VENUE RETAIL GROUP AB [1]
328	SCA AB [1]	362	SVEDBERGS AB [1]	396	WIHLBORGS FASTIGHETER AB [1]
329	SCAN MINING AB [2]	363	SWEDISH MATCH AB [1]	397	VITROLIFE AB [1]
330	SCANCEM AB [2]	364	SWEDOL AB [1]	398	VLT AB [2]
331	SCANDIACONSULT [2]	365	SVENSKA ORIENT LINJEN AB [2]	399	WM-DATA AB [2]
332	SCANDIC HOTELS [2]	366	SWITCHCORE AB [2]	400	VOLVO AB [1]
333	SCANIA AB [1]	367	SYDKRAFT AB [2]	401	VOSTOK GAS LTD. [2]
334	SECO TOOLS AB [1]	368	SYSTEMAIR AB [1]	402	XANO INDUSTRI AB [1]
335	SECTRA AB [1]	369	TECHNOLOGY NEXUS AB [2]	403	XPONCARD AB [2]
336	SECURITAS AB [1]	370	TELE2 AB [1]	404	ZETECO [2]
337	SECURITAS DIRECT AB [2]	371	TELECA AB [2]	405	ZODIAK TELEVISION AB [2]

Table B3

Excluded Firms

The table shows firms excluded from the final data set. A company name with the superscript one (1) indicates that the firm completely lacks data on one of the parameters necessary in both Datastream and Compustat. A company name with the superscript two (2) indicates that the firm reports its accounting data in another currency than SEK, signaling that it is an SDR and that the firm is domiciled in a foreign country. A company name with the superscript three (3) indicates that we have been unable to locate the firm in Datastream and Compustat. A company name with the superscript four (4) indicates that the firm does not meet the minimum data-availability requirement. The data-availability requirement all firms need to fulfill in order to be included in the annual rankings we perform each year *t*, at the end of June are: total return index at the end of June *t-1*, market capitalization at the end of December *t-1* and at the end of June *t*, total assets for *t-1* and *t-2*, total inventories for *t-1* and *t-2*, total PPE for *t-1* and *t-2*, net income before extraordinary items for *t-1* and a positive book value of equity for *t-1*. A company name with the superscript five (5) indicates that the firm was delisted prior to July 1989, i.e. delisted before our data set starts. A company name with the superscript six (6) indicates that the firm was listed after June 2010, i.e. after our data set ends. Company names occurring more than once are the results of various corporate actions (e.g. mergers or spin-offs) or simply delisted firms that later on are relisted.

Table B3 Excluded Firms

1	3K [3]
2	ABB [1]
3	ABB LTD. [2]
4	ABU GARCIA [1]
5	ABV [5]
6	ADAMAS [1]
7	ADAMSONS [3]
8	ADEPTEN [1]
9	AHLSELL A FRIA [1]
10	AINAX AB [1]
11	AKERMANS A [1]
12	AKZO NOBEL NV [1]
13	ALCATEL-LUCENT [1]
14	ALFORT & CRONHOLM [3]
15	ALLHUS B [1]
16	ALLTELE ALLM.SVEN.TELAB [1]
17	ALMEDAHL [1]
18	ALMEDAHL [3]
19	ALTIMA AB [1]
20	ANDERSON IND. BF [1]
21	ANTICIMEX F [1]
22	ARANAS BF [1]
23	ARETE AB [1]
24	ARISE WINDPOWER AB [1]
25	ARJO [4]
26	ARTEMA MEDICAL AB [1]
27	ARTINOVA [3]
28	ASKEN INV. [1]
29	ASTICUS [1]
30	ASTRAZENECA PLC. [2]
31	ATLANTICA FRB. [1]
32	AUTOFILL AB [1]
33	AUTOLIV [1]
34	AUTOLIV INCO. [1]
35	AVANZA BANK HOLDING AB [1]
36	AWAPATENT [3]
37	AVEGA GROUP AB [6]
38	AVENA [1]
39	AVESTAPOLARIT [1]
40	AXTRADE [1]
41	B & B INVEST B [1]
42	BALDER FASTIGHETS AB [1]
43	BARMKAN [3]
44	BASTIONEN BF [1]
45	BAYER AG [1]
46	BCP [1]
47	BEIJER CAPITAL [1]
48	BEIJER INDUSTRIES [3]
49	BEIJER INV [1]
50	BERGALIDEN [1]
51	BESAM [1]
52	BETONBYGG [1]
53	BEVARINGEN [1]
54	BFE BENIMA FERATOR ENGR. [1]
55	BGB I STOCKHOLM [1]
56	BLACK EARTH FARMING LTD. [2]
57	BNL INFORMATION B [1]
58	BOHUS FASTIGHETS [1]
59	BOLIDEN AB [1]
60	BOLIDEN AB [5]
61	BOSTADS AB DROTT [1]
62	BPA [1]
63	BROSTROM AB [5]
64	BRUKENS NORDIC [1]
65	BTGN [1]
66	BYGG FAST [1]
67	BYGGMAX GROUP AB [1]
68	CABANCO [1]
69	CARAN AB [1]
70	CARDO [1]
71	CARL LAMM AB [1]
72	CARL LAMM HOLDING AB [4]
73	CARNEGIE & CO [1]
74	CDON GROUP AB [6]
75	CEDERROTH NDC.BF [1]
76	CELLPOINT INCO. [1]
77	CITARENT [1]
78	COASTAL CONTACTS INCO. [2]
79	COLUMNA AB [1]
80	COMINVEST [1]
81	COMPONENTA [1]
82	CONATA [1]
83	CONNECTA [1]
84	CONSILIUM [1]
85	CONSTRUCTA BF [1]
86	CONVEXA [1]
87	CORONADO [1]
88	CRANAB [1]
89	CUSTOS AB [1]
90	D CARNEGIE & CO AB [1]
91	DACKE BF [1]
92	DATABOLIN BF [1]
93	DATACENTRALEN [3]
94	DATALOGIC [1]
95	DATEMA BF [1]
96	DEPENOVA A [1]
97	DEVH.I ALV. B [1]
98	DIAB [3]
99	DILIGENTIA [1]
100	DUNI AF [1]
101	EAST CAPITAL EXPLORER AB [1]
102	EDATA BF [1]
103	EDEBE PROM.BF [1]
104	EDSTRAND B FRIA [1]
105	ELLOS [1]
106	EMIL LUNDGRENS AB [1]
107	EMPIRE AB [1]
108	ENATOR [1]
109	ENATOR [1]
110	ENQUEST PLC. [2]
111	ENQVISTBOLAGEN [1]
112	ENSTROM [1]
113	EPICEPT CORP. [2]
114	ERNST. B [1]
115	ESSVE B [1]
116	ETRION CORPORATION [6]
117	EUROWAY BF [1]
118	EXPORT INVEST A [1]
119	FAGERHULTS IND.B [1]
120	FALUHUS [3]
121	FB BANKEN [1]
122	FINANSRUTIN [1]
123	FLAKT [5]
124	FME EUROPE AKTIEBOLAG AB [1]
125	FORCENERGY INCO. [1]
126	FORDONIA [1]
127	FORENINGS BKN.AB [1]
128	FRIGOSCANDIA [1]
129	FRISTADS [1]
130	FTGH.FORTET B [1]
131	FUNDIA [1]
132	FÖRETAGSFINANS [3]
133	GAB [3]
134	GAMBRO AB [1]
135	GAMLESTADEN [1]
136	GENERATOR [3]
137	GNOSJOE GRUPPEN BF [1]
138	GORTHON INV. [1]
139	GOTABANKEN [1]
140	GOTAGRUPPEN [1]
141	GOTIC 'B' [1]
142	GRANINGE AB [1]
143	GRAUTEN OIL AF [1]
144	GUIDE KONSULT [1]
145	GUNNEBO BRUKS [1]
146	GYLLENHAMMAR [1]
147	GYLLING OPTIMA BATTERIES [1]
148	HADRONEN SA [2]
149	HAKI [3]
150	HANDBKN.HYPOTEK [1]
151	HASSELBLAD [1]
152	HASSELFORS [1]
153	HASSELFORS [1]
154	HEBI HEALTH CARE KVB AB [1]
155	HEMGLASS [1]
156	HEMSTADEN BOSTADSAB [1]
157	HERON [1]
158	HILAB [1]
159	HNB [3]
160	HOIST INTL. [1]
161	HOIST INTL.AB [1]
162	HOLDING FINANS [1]
163	HOLMENS BRUK A [1]
164	HORDA [1]
165	HOTORGET FTGH.B [1]
166	HP FRG.OCH KI.BF [1]
167	HQ AB [1]
168	HUFVUDSTADEN INTL. [1]
169	HÖGANÄS [3]
170	IC COMPANYS A/S [2]
171	IDK DATA BF [1]
172	IGGE.BRUK B FRIA [1]
173	IMG INDE.MEDIA GROUP AB [1]
174	INDEPENDENT [1]
175	INDEPENDENT [1]
176	INDEVO [1]
177	INDRI.MATMATK.BF [1]
178	INTER CREDIT AF [1]
179	INTER INNVNS [1]
180	INTERNATIONAL PETROLEUM CORP. [3]
181	INVENT MAN. [1]
182	INVIK & CO AB [1]
183	IVARS BIL I HOTING [1]
184	JEPPSSON [1]
185	JOBLINE INTERNATIONAL [4]
186	JOHANNSON CLAES [1]
187	JOHNSON PUMP INTL. [1]
188	JOHNSON PUMP INTL. [1]
189	JP BANK [1]
190	KALLDATA [1]
191	KANTHAL [1]
192	KANTHAL [1]
193	KAP [1]
194	KAUPTHING BANK HF [2]
195	KEBO B [1]
196	KONTORSUTVECKLING [1]
197	KORSNAS MARMA [1]
198	KRAMO BF [1]
199	KVAERNER ASA [1]
200	LANDERIET FGB. [1]
201	LAWSON SOFTWARE INCO. [2]
202	LB ICON AB [1]
203	LEKSELL GOLV [1]
204	LEO FRIA [1]
205	LIC CARE [1]
206	LIFCO [1]
207	LILJEHOLMEN AB [1]
208	LIVSMEDELSKOMPANIET [3]
209	LJUNGDAHLS [3]
210	LKB [3]
211	LOGICA PLC. [2]
212	LOUIS GIBECK AB [1]
213	LUNDIN MINING CORP. [1]
214	LUXONEN SA [2]
215	M2 FASTIGHETER AB [1]
216	MALDATA B [1]
217	MALM.RED. BF [1]
218	MARABOU [1]
219	MARININVEST [3]
220	MARTINSSON GRUPPEN AB [1]
221	MATTEUS [1]
222	MAXIM PHARMS.INC [2]
223	MELKER SCHORLING AB [1]
224	MEMORY DATA [1]
225	MERCURIAS [1]
226	METO [2]
227	METRO INTERNATIONAL SA [2]
228	MILLICOM INTL.CELU.SA [1]
229	MOGUL [2]
230	MONARK STIGA AB [1]
231	MONITOR [3]
232	MOVEXA [1]
233	MQ HOLDING AB [1]
234	MUNKSJO [1]
235	NATURKOMPANIET AB [1]
236	NCB AF [1]
237	NEONET AB [1]
238	NESSIM [3]
239	NEWCAP HOLDING A/S [2]
240	NILS WEIBULL [1]
241	NISSES B [1]
242	NK CITY FASTIGHETS [4]
243	NK CITY FASTIGHETS [1]
244	NLK CELPAP AF [1]
245	NOBEL BIOCARE HOLDING AG [2]
246	NOBEL INDR.SVER.BF [1]
247	NOKIA CORPORATION [1]
248	NORDBANKEN [1]
249	NORDBANKEN [1]
250	NORDEA BANK AB [1]
251	NORDEN EXPORT [1]
252	NORDNET AB [1]
253	NORSK HYDRO ASA [1]
254	NOVESTRA AB [1]
255	NYCKLEN [1]
256	OASMIA PHARMACEUTICAL AB [1]
257	OLD MUTUAL PLC. [2]
258	OMI CORPORATION SDB [1]
259	OMX AB [2]
260	OPUS [1]
261	ORESUND INVESTMENT AB [1]
262	ORIFLAME COSMETICS SA [2]
263	OST GOTA ENSKILDA BANKEN [1]
264	OWELL [1]
265	OXIGENE INCO. [2]
266	PANG INVEST [3]
267	PAPYRUS [1]
268	PARAFRONT [1]
269	PARTNERINV [1]
270	PEAB INDUSTRI AB [4]
271	PEAK PERFORMANCE [1]
272	PENDAX [1]
273	PERFRESH [1]
274	PHARMACIA [1]
275	PHARMACIA CORP. [1]
276	PHARMACIA CORP. [2]
277	PLATZER FTGH. AB [1]
278	PLM [1]
279	PLM [5]
280	PM [1]
281	POLAR & SÄVSJÖ [3]
282	POLARATOR [1]
283	POWERWAVE TECHS.INCO. [2]
284	POYRY OYJ [2]
285	PRINTCOM AB [3]
286	PRINTCOM ETIKETT [1]
287	PRODURA [1]
288	PROGRAMATOR [1]
289	PROSOLVIA AB [1]
290	PROSPARITAS BF [1]
291	PROTORP FRV. [1]
292	PROVENTUS [1]
293	PROVIDENTIA AF [1]
294	PROVOBIS AB [1]

295 PSI GROUP ASA [2]
296 PULSEN I BORAS B [1]
297 RACKSTAHUS [1]
298 RADIOSYSTEM SWEDEN [1]
299 RATOS AB [1]
300 REALIA AB [1]
301 REINHOLD FTGH.A [1]
302 RGNB.FTGH. BF [1]
303 ROCKHAMMARS BRUKS [1]
304 RORVIKS GRUPPEN AB [1]
305 ROUND OFFICE [3]
306 SAAB SCANIA [1]
307 SAGAX AB [1]
308 SAINT GOBAIN PAPIER BOIS [1]
309 SANNDAL [1]
310 SARDUS [3]
311 SAS SVERIGE AB PUB. [1]
312 SCANDIAFELT [1]
313 SCANDINAVIA ONLINE [1]
314 SCANSPED AB [1]
315 SCAPA INTER [1]
316 SE BANKEN [1]
317 SECAB [1]
318 SIFAB [1]
319 SJOLANDERGRUPPEN [1]
320 SKANDIA FORSAKRINGS AB [1]
321 SKANDIA INTL.HDG. [1]
322 SKANSKA BANKEN A [1]
323 SKARABORGSBANKEN [1]
324 SMZ BF [1]
325 SOCIETE EUROPEENNE COMM. [1]
326 SONESSON [1]
327 SORB INDUSTRI AB [1]
328 SPCS SCANDIANVIAN PC [1]
329 SPCS-GRUPPEN [2]
330 SPIRA AB [1]
331 SPORRONG [1]
332 STADSHYPOTEK AB [1]
333 STANCIA [1]
334 STANCIA [1]
335 STIAB [1]
336 STORA ENSO OYJ [2]
337 STORHEDEN FASTIGHETS AB [1]
338 SWANBOARD MASONITE [1]
339 SWEDBANK AB [1]
340 SVEDBERGS AB [1]
341 SWEDISH MATCH AB [5]
342 SWEDSPAN INDUSTRIER [1]
343 SWEGON [1]
344 SVEN.KREDTFOR [1]
345 SVENSKA ENERGINÄT [3]
346 SVENSKA HANDBKN.AB [1]
347 SWEPART MECAN [1]
348 SVITHOID TANKERS AB [1]
349 SVOLDER AB [1]
350 SYDSVKA.DAGB. BF [1]
351 SYNECTICS MEDICAL [1]
352 SYNGENTA AG [2]
353 TANGANYIKA OIL CO.LTD. [1]
354 TAX FREE [1]
355 THOMEE HORLE [1]
356 TIETO OYJ [2]
357 TNSAT [1]
358 TRANSCOM WORLDWIDE SA [2]
359 TRESOR [3]
360 TRIGON AGRI A/S [6]
361 TRUSTOR AB [1]
362 TRYCKINVEST I NORDEN [1]
363 TRYGG-HANSA AB [1]
364 UDDEHOLM [1]
365 UNIBET GROUP PLC. [2]
366 VENCAP INDUSTRIER AB [1]
367 VERIMATION AB [1]
368 WERMIA [1]
369 WERMLANDSBANKEN [1]
370 VIAK B [1]
371 VIDE INVEST [1]
372 WILKENSON HANDSKMAKARN [1]
373 VISION PARK AB [1]
374 VOSTOK NAFTA INV.SDB LTD [1]
375 WSA [3]

Table B4

Disregarded Test Portfolios

The table shows descriptive statistics of the disregarded test portfolios. Panel A shows the average monthly returns of the quintile test portfolios, Panel B shows the average monthly returns of the decile portfolios and Panel C shows the average monthly returns of the 12 test portfolios. Panel D shows test portfolios based on a 4x4 Size and Book-to-market sort, and Panel E shows test portfolios based on a 3x4 Size and Book-to-market sort.

Table B4 Descriptive Statistics of Disregarded Test Portfolios

Panel A: Quintile Portfolios - Average Monthly Returns (%)					
	Smallest 1	2	3	4	Largest 5
Return-on-Assets	-0.73	0.60	1.82	1.14	1.16
Avg. No. of Firms	34	34	34	34	34
Investments-to-Assets	1.10	0.34	0.96	1.03	0.99
Avg. No. of Firms	34	34	34	34	34
Asset Growth	0.70	1.54	0.94	0.72	0.56
Avg. No. of Firms	34	34	34	34	34
Pre-ranking CAPM Beta	1.09	0.89	0.95	1.17	0.74
Avg. No. of Firms	34	34	34	34	34

Panel B: Decile Portfolios - Average Monthly Returns (%)										
	Smallest 1	2	3	4	5	6	7	8	9	Largest 10
Size	1.60	1.22	1.12	0.97	0.99	1.09	0.61	1.37	1.34	0.86
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17
Book-to-Market	0.45	1.46	1.53	0.84	1.57	1.16	1.29	1.21	1.21	1.71
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17
Return-on-Assets	-0.76	-0.73	0.58	0.59	1.55	1.79	1.50	1.27	1.08	1.30
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17
Investments-to-Assets	1.49	0.86	0.75	0.49	0.30	1.76	0.70	1.21	0.94	0.72
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17
Asset Growth	0.62	0.93	1.46	1.24	1.01	1.04	0.78	0.89	1.03	0.05
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17
Pre-ranking CAPM Beta	1.04	1.32	0.81	1.02	0.60	1.22	1.22	0.95	0.75	0.54
Avg. No. of Firms	17	17	17	17	17	17	17	17	17	17

Panel C: 12 Portfolios - Average Monthly Returns (%)												
	Smallest 1	2	3	4	5	6	7	8	9	10	11	Largest 12
Investments-to-Assets	1.48	0.99	0.59	0.80	0.89	0.03	1.70	1.24	1.08	0.94	0.79	0.85
Avg. No. of Firms	14	14	14	14	14	14	14	14	14	14	14	14
Pre-ranking CAPM Beta	1.11	1.02	1.78	0.93	1.01	0.57	1.45	1.02	0.98	1.18	0.98	0.20
Avg. No. of Firms	14	14	14	14	14	14	14	14	14	14	14	14

Panel D: 4x4 Portfolios Formed on Size and Book-to-Market Ratio

	Low	2	3	High		Low	2	3	High
	Average Monthly Returns (%)					Average No. of Firms Included in Portfolios			
Small	1.40	1.36	1.23	1.22	Small	6	8	11	18
2	0.92	0.99	1.01	1.12	2	9	11	11	11
3	0.52	0.93	1.22	1.26	3	13	12	11	8
Big	0.70	1.29	1.25	1.40	Big	15	12	10	7

Panel E: 3x4 Portfolios Formed on Size and Book-to-Market Ratio

	Low	2	3	High		Low	2	3	High
	Average Monthly Returns (%)					Average No. of Firms Included in Portfolios			
Small	1.22	0.51	0.65	0.57	Small	9	12	15	21
2	-0.05	0.38	0.82	0.80	2	15	15	15	13
Big	0.22	0.80	0.75	0.91	Big	19	16	13	9

Table B5

Industry Distribution

The table shows the allocation of firms to different industry groups. As can be noted the dispersion of the firms is rather limited and groups such as Electronics, Financials and Machinery & Equipment contain most of the companies. The Industry Code column shows the industry code as given by Datastream's mnemonic WC06011.

Table B5 Industry Distribution

INDUSTRY DISTRIBUTION		
INDUSTRY CODE	INDUSTRY	NUMBER
4000	ELECTRONICS	79
8500	MISCELLANEOUS	68
4300	FINANCIAL	44
4900	MACHINERY & EQUIPMENT	30
2800	CONSTRUCTION	19
3400	DRUGS, COSMETICS & HEALTH CARE	18
7900	TRANSPORTATION	17
6100	PAPER	15
5500	METAL PRODUCT MANUFACTURERS	13
7000	RETAILERS	13
8200	UTILITIES	13
3700	ELECTRICAL	12
3100	DIVERSIFIED	9
6400	PRINTING & PUBLISHING	9
6700	RECREATION	9
5200	METAL PRODUCERS	8
4600	FOOD	6
5800	OIL, GAS, COAL & RELATED SERVICES	6
7300	TEXTILES	5
2500	CHEMICALS	4
1900	AUTOMOTIVE	3
1300	AEROSPACE	2
1600	APPAREL	1
2200	BEVERAGES	1
7600	TOBACCO	1
	SUM	405

Table B6

Model Factors – Descriptive Statistics

The table shows descriptive statistics for the model factor portfolios. The means and standard deviations below are provided in percent and are based on observations over 259 months.

Table B6 Model Factors – Descriptive Statistics

Factor Portfolio	Monthly Mean Excess Return	Std Dev	*t*-stat for Mean = 0	Cross-Correlations R_M	SMB	HML	PR1YR	INV	ROA
R_M	0.36	6.43	0.89	1.00					
SMB	-0.01	4.56	0.89	-0.18	1.00				
HML	0.41	6.56	-0.04	-0.30	0.00	1.00			
PR1YR	0.91	10.45	1.00	-0.26	0.01	0.22	1.00		
INV	0.47	4.89	1.40	0.22	0.02	-0.17	-0.31	1.00	
ROA	1.08	6.59	1.55	-0.29	-0.18	0.32	0.44	-0.46	1.00

Table B7

Size and Book-to-Market Test Portfolios

The table shows the results of the Book-to-Market test portfolios. Panel A contains the summary statistics. Panel B shows the results of the slightly modified Alternative three-factor model, Panel C the results of the CAPM, Panel D the results of the Fama French three-factor model and Panel E the results of the Carhart four-factor model. An estimate is significant on the 5% significance level if the absolute value of its *t*-test statistic is equal to or greater than 1.97. All *t*-test statistics are adjusted for heteroscedasticity.

Table B7 Size and Book-to-Market Portfolios

	Book-to-Market Equity Terciles							
Size	Low	2	High	H-L	Low	2	High	H-L
Panel A: Summary Statistics								
	Means				Standard Deviations			
Small	1.15	0.65	0.48	-0.67	11.97	8.03	7.00	10.19
2	-0.02	0.66	0.73	0.76	8.56	7.97	7.34	6.43
Big	0.30	0.79	0.77	0.46	9.69	7.06	7.16	8.60
	Average No. of Firms Included in Portfolios							
Small	13	18	26					
2	19	20	18					
Big	25	19	13					

	Book-to-Market Equity Terciles									
Size	Low	2	High	H-L	Low	2	High	H-L	F_{GRS}	$p(GRS)$
Panel B: Regression $R_{it}^{e} = \alpha_i + \beta_{iM} R_{Mt}^{e} + \beta_{iINV} INV_t + \beta_{iROA} ROA_t + \varepsilon_{it}$										
	α_i				t_{α_i}					
Small	1.23	0.71	0.35	-0.88	2.19	2.20	1.00	-1.53	1.784	0.051
2	0.00	0.51	0.75	0.76	-0.01	1.60	2.39	1.83		
Big	0.07	0.27	0.52	0.45	0.18	1.29	1.87	0.77		
	β_{iM}				$t_{\beta_{iM}}$					
Small	0.95	0.80	0.68	-0.27	5.05	12.91	9.24	-1.20		
2	0.97	0.95	0.80	-0.17	12.67	16.71	10.70	-1.69		
Big	1.18	0.97	0.85	-0.32	15.71	19.90	14.86	-2.78		
	β_{iINV}				$t_{\beta_{iINV}}$					
Small	0.12	0.04	0.06	-0.06	0.90	0.41	0.79	-0.48		
2	-0.04	0.00	-0.08	-0.04	-0.63	0.04	-1.28	-0.41		
Big	0.07	0.12	0.03	-0.04	0.44	1.44	0.31	-0.18		
	β_{iROA}				$t_{\beta_{iROA}}$					
Small	-0.44	-0.34	-0.13	0.31	-4.89	-5.77	-1.76	3.30		
2	-0.32	-0.17	-0.24	0.07	-5.02	-2.59	-3.49	0.72		
Big	-0.20	0.11	-0.07	0.14	-1.73	2.05	-1.12	0.92		
	R^2				RMSE					
Small	0.41	0.61	0.46	0.10	9.21	5.03	5.18	9.73		
2	0.68	0.68	0.60	0.05	4.88	4.57	4.68	6.31		
Big	0.71	0.78	0.62	0.09	5.28	3.34	4.42	8.26		

Size	Book-to-Market Equity Terciles									
	Low	2	High	H-L	Low	2	High	H-L	F_{GRS}	$p(GRS)$
	Panel C: Regression $R^e_{it} = \alpha_i + \beta_{iM} R^e_{Mt} + \varepsilon_{it}$									
	α_i				t_{α_i}					
Small	0.76	0.32	0.22	-0.54	1.31	0.96	0.69	-0.91	1.090	0.369
2	-0.40	0.30	0.43	0.83	-1.23	1.06	1.46	2.14		
Big	-0.14	0.45	0.46	0.60	-0.42	2.17	1.67	1.18		
	β_{iM}				$t_{\beta_{iM}}$					
Small	1.10	0.91	0.72	-0.38	6.10	13.87	9.60	-1.73		
2	1.06	1.00	0.85	-0.20	14.69	16.99	10.77	-2.05		
Big	1.25	0.96	0.88	-0.37	16.11	20.58	15.96	-3.22		
	R^2				RMSE					
Small	0.35	0.53	0.44	0.06	9.68	5.50	5.25	9.92		
2	0.63	0.66	0.56	0.04	5.23	4.68	4.88	6.31		
Big	0.68	0.77	0.62	0.08	5.46	3.40	4.43	8.28		

Size	Book-to-Market Equity Terciles									
	Low	2	High	H-L	Low	2	High	H-L	F_{GRS}	$p(GRS)$
	Panel D: Regression $R^e_{it} = \alpha_i + \beta_{iM} R^e_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_{it}$									
	α_i				t_{α_i}					
Small	1.04	0.31	0.06	-0.98	2.06	1.28	0.29	-1.86	1.034	0.419
2	-0.25	0.18	0.24	0.49	-1.02	0.82	1.06	1.67		
Big	0.24	0.33	0.24	0.00	1.32	1.81	1.08	-0.01		
	β_{iM}				$t_{\beta_{iM}}$					
Small	1.02	1.01	0.91	-0.11	6.37	25.12	21.64	-0.67		
2	1.03	1.14	1.02	-0.01	18.94	21.46	17.22	-0.10		
Big	1.00	1.01	0.99	0.00	23.30	30.86	22.64	-0.04		
	β_{iSMB}				$t_{\beta_{iSMB}}$					
Small	0.77	0.86	0.83	0.07	3.48	15.66	12.83	0.30		
2	0.60	0.62	0.56	-0.04	9.02	8.28	7.96	-0.41		
Big	-0.23	-0.17	-0.09	0.14	-3.39	-3.40	-1.40	1.53		
	β_{iHML}				$t_{\beta_{iHML}}$					
Small	-0.59	-0.04	0.25	0.84	-4.84	-0.71	6.54	6.59		
2	-0.33	0.19	0.32	0.65	-6.70	4.57	6.15	10.30		
Big	-0.72	0.24	0.42	1.14	-13.10	5.15	7.98	18.53		
	R^2				RMSE					
Small	0.54	0.77	0.76	0.32	8.20	3.91	3.42	8.43		
2	0.80	0.80	0.74	0.44	3.89	3.63	3.76	4.82		
Big	0.91	0.83	0.76	0.77	2.97	2.96	3.54	4.17		

	Book-to-Market Equity Terciles									
Size	Low	2	High	H-L	Low	2	High	H-L	F_{GRS}	$p(GRS)$
	Panel E: Regression $R^e_{it} = \alpha_i + \beta_{iM} R^e_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iPR1YR} PR1YR_t + \varepsilon_{it}$									
	α_i				t_{α_i}					
Small	1.07	0.40	0.08	-0.99	2.07	1.64	0.39	-1.84	1.176	0.301
2	-0.18	0.25	0.31	0.49	-0.77	1.15	1.32	1.63		
Big	0.27	0.36	0.32	0.06	1.41	1.94	1.47	0.23		
	β_{iM}				$t_{\beta_{iM}}$					
Small	1.00	0.98	0.90	-0.10	6.77	24.00	21.67	-0.69		
2	1.01	1.12	1.00	-0.01	18.35	22.08	17.45	-0.08		
Big	0.99	1.00	0.96	-0.03	22.43	29.97	21.84	-0.45		
	β_{iSMB}				$t_{\beta_{iSMB}}$					
Small	0.77	0.85	0.83	0.07	3.44	14.63	12.73	0.30		
2	0.60	0.61	0.56	-0.04	8.79	7.89	7.89	-0.41		
Big	-0.23	-0.17	-0.09	0.13	-3.37	-3.36	-1.46	1.46		
	β_{iHML}				$t_{\beta_{iHMl}}$					
Small	-0.58	-0.02	0.26	0.84	-4.66	-0.36	6.91	6.43		
2	-0.32	0.21	0.33	0.65	-6.46	5.38	6.68	9.99		
Big	-0.72	0.24	0.44	1.16	-13.46	5.49	10.12	19.24		
	β_{iPR1YR}				$t_{\beta_{iPR1YR}}$					
Small	-0.04	-0.09	-0.02	0.01	-0.57	-2.51	-0.97	0.19		
2	-0.07	-0.07	-0.07	0.00	-2.09	-2.82	-2.03	0.06		
Big	-0.02	-0.03	-0.09	-0.06	-0.91	-1.38	-2.79	-2.40		
	R^2				RMSE					
Small	0.54	0.78	0.77	0.32	8.20	3.82	3.42	8.45		
2	0.80	0.80	0.75	0.44	3.84	3.56	3.71	4.83		
Big	0.91	0.83	0.77	0.77	2.97	2.95	3.43	4.13		

Figure B1

Predicted vs. Average Excess Returns - Size and Book-to-Market Test Portfolios

The figures show each model's excess return predictions relative to the average realized returns for the nine test portfolios double sorted on size and book-to-market ratio. The figures display the pricing ability of our slightly adjusted alternative three-factor (A3F) model, the CAPM, the Fama-French three-factor (FF3F) model and the Carhart four-factor (C4F) model as the alphas are given by each observation's deviation from the forty-five degree line. In a perfectly defined model, all observations should lie along the line. The predicted monthly excess return (%) is plotted on the x-axis and the average realized monthly return (%) is plotted on the y-axis.

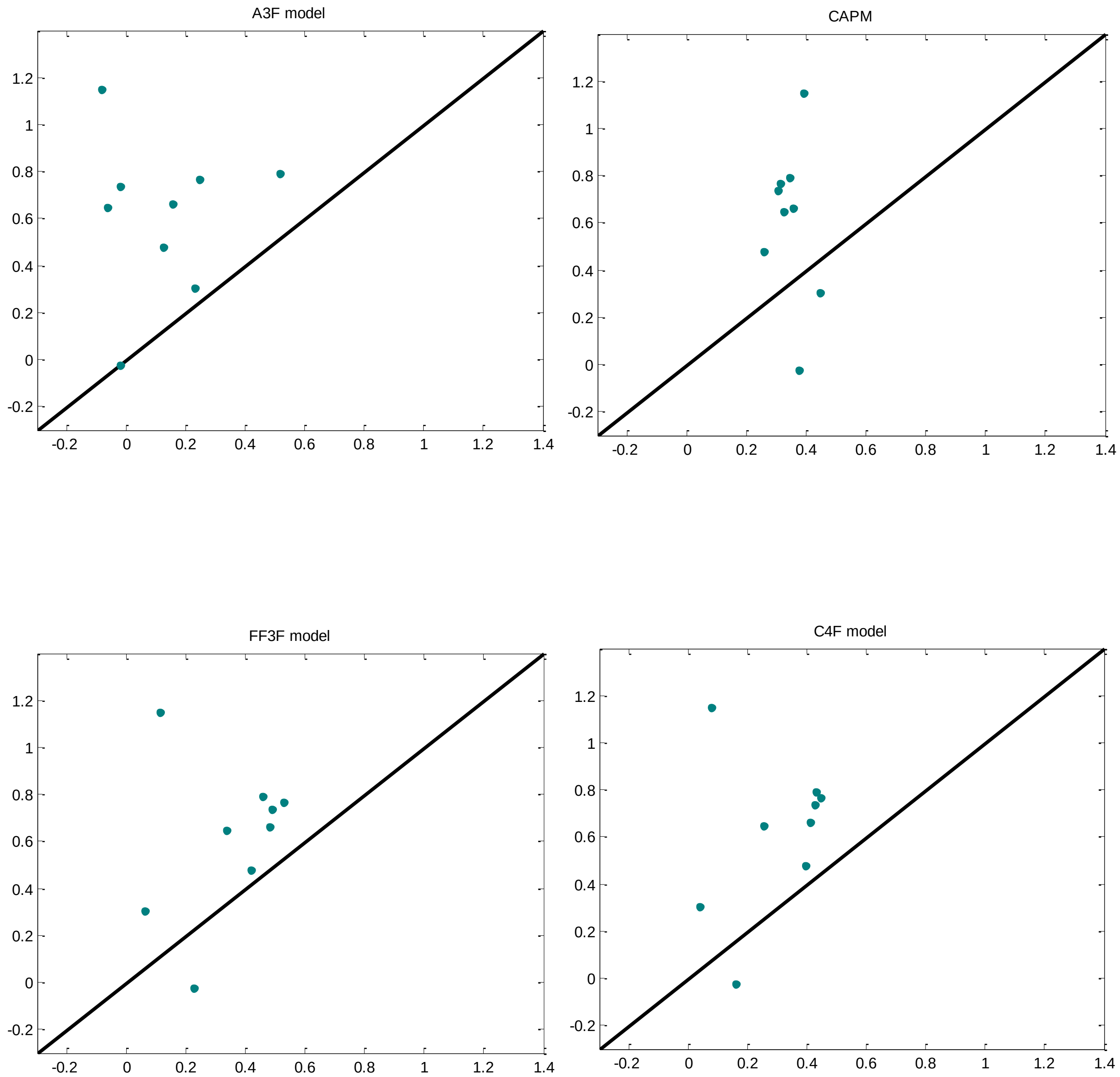

Table B8

Asset Growth Test Portfolios

The table shows the results of the Asset Growth test portfolios for our slightly modified Alternative three-factor model as well as for the benchmark models. An estimate is significant on the 5% significance level if the absolute value of its *t*-test statistic is equal to or greater than 1.97. All *t*-test statistics are adjusted for heteroscedasticity.

Table B8 Asset Growth Portfolios

	Asset Growth - Twelve Portfolios														
	1	2	3	4	5	6	7	8	9	10	11	12	H-L	F_{GRS}	$p(GRS)$
Avg. No of firms in Portfolio	14	14	14	14	14	14	14	14	14	14	14	14			
Mean	-0.02	0.29	1.60	0.26	1.11	0.38	0.43	1.27	-0.08	0.62	0.36	-0.60	-0.57		
Std Dev	11.15	10.39	8.53	9.59	11.15	8.73	8.45	8.53	9.58	11.12	8.24	10.44	11.47		
α_{ALT}	0.03	-0.47	1.22	0.29	0.65	0.06	0.05	0.82	-0.15	0.56	0.35	-0.47	-0.49	1.897	0.031
β_{MKT}	0.84	0.85	0.88	0.91	1.09	1.00	1.04	1.00	1.13	1.18	1.01	0.88	0.04		
β_{INV}	0.33	0.78	0.25	0.14	0.64	-0.06	0.02	0.03	-0.27	-0.17	-0.35	-0.07	-0.40		
β_{ROA}	-0.47	0.09	-0.05	-0.39	-0.22	-0.01	0.00	0.08	-0.19	-0.26	-0.17	-0.38	0.09		
$t_{\alpha_{ALT}}$	0.05	-0.85	3.51	0.59	1.30	0.16	0.14	2.31	-0.34	0.97	1.13	-0.86	-0.71		
$t_{\beta_{MKT}}$	8.93	10.43	12.41	13.53	15.77	11.89	14.97	15.15	11.27	14.08	18.40	9.07	0.29		
$t_{\beta_{INV}}$	2.46	4.36	2.17	1.13	2.18	-0.53	0.25	0.34	-2.03	-0.92	-3.57	-0.63	-2.15		
$t_{\beta_{ROA}}$	-2.81	0.74	-0.64	-2.16	-1.27	-0.21	0.00	1.08	-1.87	-1.61	-2.68	-2.31	0.55		
R^2	0.48	0.46	0.53	0.58	0.65	0.54	0.64	0.56	0.60	0.52	0.65	0.41	0.04		
$RMSE$	8.10	7.65	5.90	6.25	6.68	5.95	5.13	5.72	6.06	7.72	4.92	8.04	11.32		
α_{CAPM}	-0.39	-0.05	1.26	-0.11	0.66	0.02	0.06	0.92	-0.49	0.18	0.01	-0.95	-0.56	2.146	0.012
β_{MKT}	1.04	0.96	0.94	1.05	1.26	1.00	1.05	0.99	1.14	1.23	1.00	0.98	-0.05		
$t_{\alpha_{CAPM}}$	-0.71	-0.10	3.38	-0.27	1.42	0.07	0.19	2.61	-1.31	0.37	0.02	-1.81	-0.78		
$t_{\beta_{MKT}}$	9.86	8.98	13.45	14.25	11.75	12.17	17.00	15.54	11.31	12.71	18.13	10.07	-0.38		
R^2	0.36	0.35	0.50	0.50	0.53	0.54	0.64	0.55	0.58	0.50	0.61	0.37	0.00		
$RMSE$	8.96	8.39	6.04	6.82	7.68	5.93	5.11	5.71	6.19	7.84	5.14	8.33	11.49		
α_{FF}	-0.39	-0.07	1.16	-0.08	0.68	-0.08	0.13	1.05	-0.34	0.35	0.09	-0.66	-0.27	2.106	0.014
β_{MKT}	1.09	0.97	1.00	1.01	1.25	1.08	1.00	0.91	1.04	1.12	0.95	0.84	-0.25		
β_{SMB}	0.51	0.03	-0.02	-0.21	-0.01	0.17	-0.08	0.02	-0.11	-0.05	-0.02	0.20	-0.31		
β_{HML}	-0.03	0.03	0.20	-0.04	-0.04	0.19	-0.13	-0.25	-0.28	-0.32	-0.15	-0.56	-0.53		
$t_{\alpha_{FF}}$	-0.71	-0.13	3.10	-0.19	1.31	-0.22	0.41	3.18	-0.90	0.70	0.28	-1.38	-0.41		
$t_{\beta_{MKT}}$	11.13	9.95	14.38	15.96	14.87	12.22	17.77	12.96	13.54	15.94	16.72	10.22	-2.08		
$t_{\beta_{SMB}}$	4.17	0.30	-0.28	-2.20	-0.09	1.37	-0.97	0.24	-0.95	-0.46	-0.21	1.84	-2.06		
$t_{\beta_{HML}}$	-0.16	0.29	2.73	-0.24	-0.24	2.00	-1.44	-3.68	-2.01	-2.01	-1.98	-3.57	-3.17		
R^2	0.40	0.35	0.52	0.51	0.53	0.56	0.65	0.59	0.62	0.54	0.63	0.49	0.09		
$RMSE$	8.69	8.42	5.92	6.77	7.71	5.80	5.06	5.50	5.95	7.61	5.07	7.51	10.98		
α_{CAR}	-0.21	0.14	1.23	0.06	0.87	-0.02	0.16	0.94	-0.25	0.26	0.07	-0.58	-0.36	2.009	0.021
β_{MKT}	1.02	0.89	0.97	0.95	1.17	1.05	0.99	0.96	1.01	1.16	0.96	0.80	-0.22		
β_{SMB}	0.50	0.01	-0.03	-0.23	-0.02	0.16	-0.08	0.03	-0.11	-0.04	-0.02	0.20	-0.30		
β_{HML}	0.02	0.09	0.22	0.00	0.01	0.20	-0.12	-0.28	-0.25	-0.34	-0.16	-0.54	-0.55		
β_{PR1YR}	-0.19	-0.22	-0.08	-0.16	-0.21	-0.06	-0.03	0.12	-0.09	0.09	0.02	-0.09	0.10		
$t_{\alpha_{CAR}}$	-0.37	0.27	3.42	0.13	1.54	-0.06	0.47	2.93	-0.66	0.55	0.21	-1.17	-0.56		
$t_{\beta_{MKT}}$	9.27	10.14	13.95	12.10	15.37	12.25	15.75	13.98	13.59	14.17	16.79	8.94	-1.80		
$t_{\beta_{SMB}}$	4.11	0.13	-0.34	-2.37	-0.26	1.34	-0.98	0.37	-1.03	-0.40	-0.20	1.78	-1.99		
$t_{\beta_{HML}}$	0.10	0.81	3.05	-0.02	0.04	2.13	-1.46	-4.13	-1.86	-2.13	-2.03	-3.75	-3.37		
$t_{\beta_{PR1YR}}$	-1.83	-3.16	-1.80	-1.46	-1.76	-1.29	-0.50	3.13	-1.82	0.79	0.58	-1.06	1.07		
R^2	0.43	0.40	0.53	0.53	0.56	0.57	0.65	0.61	0.63	0.54	0.63	0.50	0.10		
$RMSE$	8.49	8.14	5.88	6.60	7.44	5.77	5.06	5.38	5.89	7.57	5.08	7.47	10.95		

Figure B2

Predicted vs. Average Excess Returns – Asset Growth Test Portfolios

The figures show each model's excess return predictions relative to the average realized returns for the twelve test portfolios sorted on asset growth. The figures display the pricing ability of our slightly adjusted alternative three-factor (A3F) model, the CAPM, the Fama-French three-factor (FF3F) model and the Carhart four-factor (C4F) model as the alphas are given by each observation's deviation from the forty-five degree line. In a perfectly defined model, all observations should lie along the line. The predicted monthly excess return (%) is plotted on the x-axis and the average realized monthly return (%) is plotted on the y-axis.

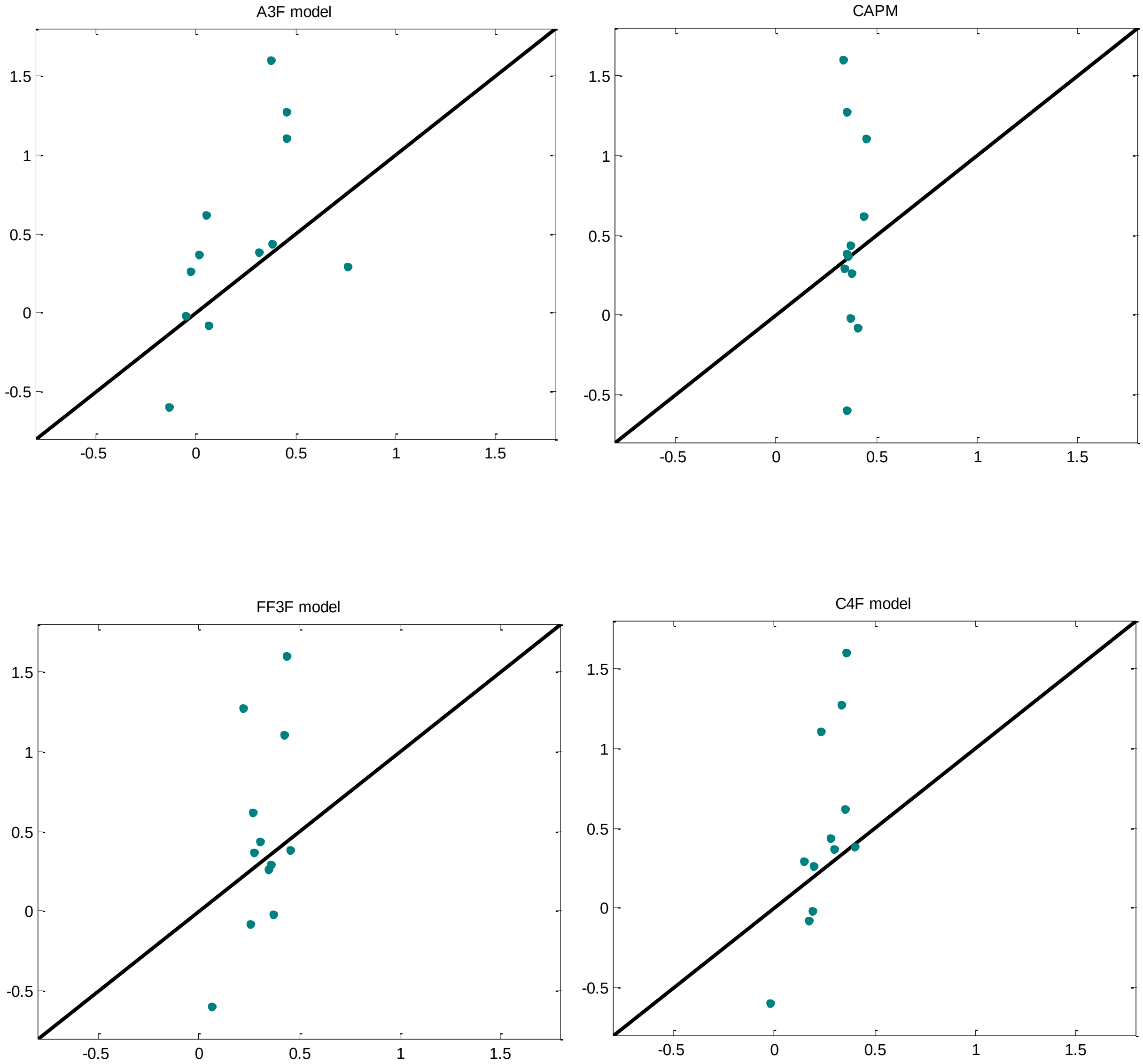

Table B9

Return-on-Assets Test Portfolios

The table shows the results of the Return-on-Assets test portfolios for our slightly modified Alternative three-factor model as well as for the benchmark models. An estimate is significant on the 5% significance level if the absolute value of its *t*-test statistic is equal to or greater than 1.97. All *t*-test statistics are adjusted for heteroscedasticity.

Table B9 Return-on-Assets Portfolios

	Return-on-Assets - Twelve Portfolios														
	1	2	3	4	5	6	7	8	9	10	11	12	H-L	F_{GRS}	$p(GRS)$
Avg. No of firms in Portfolio	14	14	14	14	14	14	14	14	14	14	14	14			
Mean	-1.00	-0.54	-0.78	0.96	0.29	0.90	1.01	0.86	1.44	0.22	0.68	0.77	1.77		
Std Dev	12.97	12.69	12.20	12.10	9.43	8.65	8.47	8.32	9.26	8.25	7.59	7.37	11.85		
α_{ALT}	-0.58	0.36	-0.44	0.55	-0.50	0.65	0.79	0.57	1.00	-0.25	0.30	0.41	0.99	2.215	0.010
β_{MKT}	0.91	0.87	1.11	1.11	1.01	1.00	0.95	1.09	1.08	1.02	0.88	0.84	-0.08		
β_{INV}	0.24	-0.09	0.06	0.61	0.53	0.04	-0.05	-0.09	-0.05	0.05	-0.03	-0.15	-0.38		
β_{ROA}	-0.79	-1.09	-0.71	-0.26	0.16	-0.12	-0.09	-0.05	0.07	0.08	0.07	0.12	0.91		
$t_{\alpha_{ALT}}$	-0.94	0.65	-0.81	0.99	-1.19	1.79	1.92	2.09	2.32	-0.77	0.79	1.24	1.50		
$t_{\beta_{MKT}}$	7.59	11.53	10.77	12.34	13.19	10.69	10.92	17.05	14.77	16.27	12.38	14.37	-0.63		
$t_{\beta_{INV}}$	1.05	-0.61	0.44	1.60	3.96	0.35	-0.36	-1.17	-0.38	0.40	-0.29	-1.57	-1.84		
$t_{\beta_{ROA}}$	-4.27	-7.03	-4.40	-1.39	1.45	-1.37	-0.91	-0.95	0.75	1.34	0.75	1.36	5.14		
R^2	0.53	0.64	0.63	0.58	0.58	0.60	0.54	0.71	0.54	0.62	0.53	0.49	0.37		
$RMSE$	8.97	7.70	7.45	7.91	6.16	5.47	5.77	4.48	6.33	5.13	5.22	5.31	9.46		
α_{CAPM}	-1.42	-0.96	-1.25	0.49	-0.09	0.53	0.67	0.47	1.06	-0.14	0.37	0.49	1.91	2.890	0.001
β_{MKT}	1.19	1.18	1.33	1.30	1.06	1.04	0.97	1.09	1.05	1.01	0.86	0.78	-0.41		
$t_{\alpha_{CAPM}}$	-2.18	-1.55	-2.30	0.94	-0.21	1.59	1.92	1.69	2.73	-0.43	1.13	1.46	2.66		
$t_{\beta_{MKT}}$	8.68	9.82	12.30	9.92	13.77	11.82	11.75	17.58	15.18	15.85	12.95	13.40	-2.77		
R^2	0.34	0.36	0.49	0.47	0.52	0.60	0.54	0.71	0.53	0.61	0.53	0.46	0.05		
$RMSE$	10.52	10.20	8.74	8.80	6.56	5.51	5.77	4.48	6.33	5.13	5.23	5.43	11.58		
α_{FF}	-1.06	-0.70	-1.03	0.55	-0.09	0.41	0.77	0.50	1.15	-0.15	0.37	0.67	1.73	3.278	0.000
β_{MKT}	1.05	1.07	1.22	1.26	1.05	1.11	0.90	1.07	0.99	1.01	0.85	0.65	-0.40		
β_{SMB}	0.72	0.40	0.22	0.00	-0.09	0.03	-0.05	-0.10	-0.14	-0.02	-0.03	-0.22	-0.94		
β_{HML}	-0.74	-0.53	-0.45	-0.11	0.01	0.22	-0.20	-0.04	-0.15	0.02	0.00	-0.33	0.42		
$t_{\alpha_{FF}}$	-1.87	-1.12	-1.97	0.96	-0.21	1.22	2.09	1.82	2.89	-0.48	1.11	2.13	2.59		
$t_{\beta_{MKT}}$	10.04	12.01	13.23	11.76	14.03	14.98	16.86	18.43	17.44	18.58	12.68	12.26	-3.34		
$t_{\beta_{SMB}}$	5.60	2.70	1.85	-0.02	-1.09	0.23	-0.63	-1.26	-1.93	-0.31	-0.47	-2.57	-6.35		
$t_{\beta_{HML}}$	-4.07	-2.50	-3.03	-0.60	0.07	2.40	-1.32	-0.56	-1.23	0.28	0.01	-4.05	2.10		
R^2	0.55	0.45	0.55	0.48	0.52	0.62	0.56	0.71	0.55	0.62	0.53	0.55	0.23		
$RMSE$	8.80	9.46	8.23	8.81	6.57	5.36	5.65	4.47	6.26	5.15	5.25	4.98	10.43		
α_{CAR}	-0.81	-0.56	-0.86	0.77	0.07	0.51	0.80	0.48	1.00	-0.08	0.39	0.49	1.31	3.082	0.000
β_{MKT}	0.95	1.01	1.15	1.18	0.99	1.07	0.89	1.07	1.04	0.99	0.85	0.72	-0.24		
β_{SMB}	0.70	0.39	0.21	-0.02	-0.10	0.02	-0.05	-0.10	-0.13	-0.02	-0.04	-0.21	-0.91		
β_{HML}	-0.68	-0.50	-0.41	-0.06	0.05	0.25	-0.19	-0.04	-0.19	0.04	0.00	-0.37	0.31		
β_{PR1YR}	-0.26	-0.15	-0.18	-0.23	-0.16	-0.11	-0.03	0.02	0.15	-0.07	-0.02	0.19	0.45		
$t_{\alpha_{CAR}}$	-1.46	-0.86	-1.59	1.24	0.18	1.48	2.12	1.77	2.68	-0.27	1.12	1.73	2.17		
$t_{\beta_{MKT}}$	8.77	10.87	11.49	13.07	13.34	15.01	16.54	17.87	16.22	18.52	11.72	14.36	-2.06		
$t_{\beta_{SMB}}$	5.28	2.71	1.67	-0.16	-1.31	0.15	-0.66	-1.23	-1.76	-0.40	-0.49	-2.80	-6.63		
$t_{\beta_{HML}}$	-4.45	-2.39	-3.25	-0.37	0.59	3.01	-1.27	-0.62	-1.50	0.50	0.09	-5.15	2.13		
$t_{\beta_{PR1YR}}$	-2.64	-1.72	-1.72	-1.75	-3.00	-2.15	-0.56	0.48	1.77	-1.65	-0.37	4.73	4.19		
R^2	0.59	0.46	0.57	0.51	0.55	0.64	0.56	0.72	0.57	0.62	0.53	0.61	0.37		
$RMSE$	8.42	9.36	8.06	8.52	6.37	5.26	5.66	4.47	6.09	5.11	5.25	4.62	9.45		

Figure B3

Predicted vs. Average Excess Returns – Return-on-Assets Test Portfolios

The figures show each model's excess return predictions relative to the average realized returns for the twelve test portfolios sorted on return-on-assets ratio. The figures display the pricing ability of our slightly adjusted alternative three-factor (A3F) model, the CAPM, the Fama-French three-factor (FF3F) model and the Carhart four-factor (C4F) model as the alphas are given by each observation's deviation from the forty-five degree line. In a perfectly defined model, all observations should lie along the line. The predicted monthly excess return (%) is plotted on the x-axis and the average realized monthly return (%) is plotted on the y-axis.

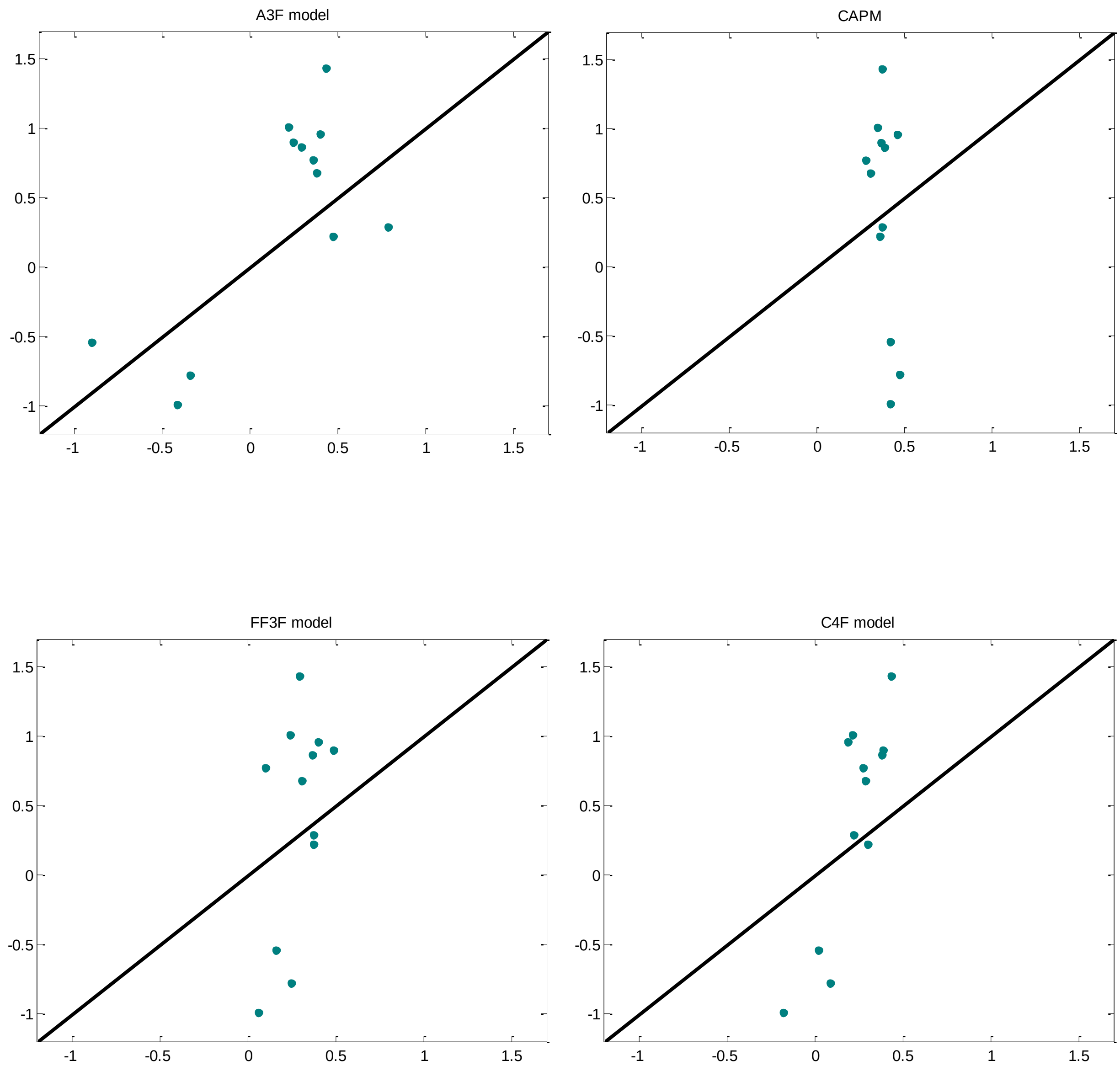

Table B10

Factor Redundancy

The table shows the results of the factor redundancy tests. Panel A shows the estimates and the R-squared values and Panel B shows the t-statistics and root mean square error. An estimate is significant on the 5% significance level if the absolute value of its *t*-test statistic is equal to or greater than 1.97. All *t*-test statistics are adjusted for heteroscedasticity.

Table B10 Factor Redundancy

				Panel A: Factor Redundancy Test - Estimates and R^2				
	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{INV}	β_{ROA}	R^2
INV	0.41	0.17						0.05
	0.84						-0.34	0.21
	0.79	0.08					-0.32	0.22
	0.41	0.18	0.07					0.05
	0.45	0.15	0.06	-0.09				0.07
	0.56	0.11	0.05	-0.06	-0.12			0.12
	0.81	0.06	-0.04	0.00	-0.05		-0.29	0.23
ROA	1.19	-0.29						0.08
	1.37					-0.62		0.21
	1.41	-0.20				-0.56		0.24
	1.20	-0.34	-0.34					0.14
	1.07	-0.26	-0.32	0.24				0.19
	0.86	-0.18	-0.31	0.19	0.22			0.30
	1.10	-0.14	-0.28	0.16	0.17	-0.42		0.39
SMB	0.04	-0.13						0.03
	0.06	-0.14		-0.04				0.04
	0.07	-0.15		-0.04	-0.02			0.04
	0.04	-0.15		-0.03	-0.01	0.05		0.04
	0.26	-0.17		0.00	0.03	-0.04	-0.20	0.09
HML	0.52	-0.31						0.09
	0.52	-0.32	-0.08					0.09
	0.42	-0.28	-0.07		0.09			0.11
	0.48	-0.26	-0.06		0.08	-0.10		0.12
	0.21	-0.22	0.00		0.04	-0.01	0.22	0.15
PR1YR	1.06	-0.43						0.07
	1.07	-0.44	-0.10					0.07
	0.94	-0.37	-0.08	0.24				0.09
	1.18	-0.29	-0.04	0.20		-0.52		0.15
	0.47	-0.19	0.11	0.09		-0.24	0.54	0.23

Panel B: Factor Redundancy Test - t-stats and RMSE								
	t_{α}	$t_{\beta_{MKT}}$	$t_{\beta_{SMB}}$	$t_{\beta_{HML}}$	$t_{\beta_{PR1YR}}$	$t_{\beta_{INV}}$	$t_{\beta_{ROA}}$	RMSE
INV	1.42	2.63						4.78
	2.80						-5.84	4.36
	2.73	1.30					-5.68	4.34
	1.41	2.67	0.84					4.78
	1.46	2.83	0.76	-0.85				4.76
	1.76	2.40	0.65	-0.60	-2.35			4.62
	2.70	1.17	-0.52	-0.03	-0.94		-4.31	4.34
ROA	3.06	-4.14						6.33
	3.90					-4.75		5.88
	4.15	-3.26				-4.45		5.75
	3.19	-4.76	-3.61					6.15
	2.76	-3.82	-3.28	1.95				5.97
	2.31	-2.73	-3.26	1.72	3.76			5.56
	3.18	-2.09	-3.62	1.89	2.84	-3.42		5.22
SMB	0.13	-2.30						4.50
	0.21	-2.26		-0.73				4.50
	0.26	-2.36		-0.65	-0.52			4.50
	0.16	-2.42		-0.58	-0.30	0.64		4.51
	0.90	-2.87		0.02	0.68	-0.52	-2.87	4.39
HML	1.35	-3.36						6.26
	1.36	-3.31	-0.73					6.27
	1.05	-3.17	-0.65		1.33			6.21
	1.12	-2.74	-0.58		1.08	-0.63		6.20
	0.49	-2.31	0.02		0.57	-0.03	2.07	6.10
PR1YR	1.70	-3.54						10.10
	1.70	-3.63	-0.65					10.11
	1.47	-3.26	-0.51	1.35				10.02
	1.89	-2.69	-0.29	1.14		-2.97		9.72
	0.74	-1.82	0.71	0.60		-1.05	3.06	9.27

Table B11

A Proposed Two-Factor Model

The table shows the results of the proposed two-factor model. Panel A, B and C show the results from testing the model on test portfolios sorted on size and book-to-market ratio, asset growth and return-on-assets ratio respectively. An estimate is significant on the 5% significance level if the absolute value of its *t*-test statistic is equal to or greater than 1.97. All *t*-test statistics are adjusted for heteroscedasticity.

Table B11 A Proposed Two-Factor Model

Panel A: Size and Book-to-Market - 3x3 Portfolios

	Book-to-Market Equity Terciles									
Size	Low	2	High	H-L	Low	2	High	H-L	F_{GRS}	$p(GRS)$
	α_i				t_{α_i}					
Small	1.33	0.75	0.40	-0.93	2.48	2.32	1.12	-1.68	1.951	0.029
2	-0.04	0.51	0.69	0.72	-0.12	1.66	2.22	1.77		
Big	0.13	0.37	0.55	0.42	0.33	1.82	2.00	0.77		
	β_{iM}				$t_{\beta_{iM}}$					
Small	0.96	0.81	0.68	-0.28	5.14	12.97	9.45	-1.22		
2	0.97	0.95	0.79	-0.18	12.75	17.36	10.73	-1.74		
Big	1.18	0.98	0.85	-0.33	16.87	20.32	15.62	-3.02		
	β_{iROA}				$t_{\beta_{iROA}}$					
Small	-0.48	-0.36	-0.15	0.33	-5.57	-6.83	-1.98	3.40		
2	-0.31	-0.17	-0.22	0.09	-5.26	-2.75	-3.21	0.86		
Big	-0.22	0.07	-0.08	0.15	-1.96	1.47	-1.39	1.04		
	R^2				RMSE					
Small	0.41	0.61	0.46	0.10	9.21	5.02	5.17	9.71		
2	0.68	0.68	0.60	0.05	4.87	4.56	4.69	6.30		
Big	0.71	0.77	0.62	0.09	5.28	3.38	4.42	8.24		

Panel B: Asset Growth - Twelve Portfolios

	1	2	3	4	5	6	7	8	9	10	11	12	H-L	F_{GRS}	$p(GRS)$
α_{ALT2}	0.29	0.14	1.42	0.39	1.16	0.02	0.07	0.84	-0.36	0.43	0.07	-0.52	-0.81	2.222	0.009
β_{MKT}	0.87	0.91	0.90	0.92	1.14	1.00	1.05	1.01	1.11	1.17	0.99	0.88	0.01		
β_{ROA}	-0.57	-0.16	-0.13	-0.43	-0.42	0.00	-0.01	0.06	-0.11	-0.21	-0.05	-0.36	0.21		
$t_{\alpha_{ALT2}}$	0.51	0.25	3.89	0.84	2.17	0.05	0.19	2.39	-0.88	0.77	0.22	-0.97	-1.15		
$t_{\beta_{MKT}}$	8.99	8.92	12.54	13.74	11.89	12.24	15.17	15.21	11.24	14.19	18.24	8.74	0.07		
$t_{\beta_{ROA}}$	-3.59	-1.39	-1.90	-2.58	-2.85	0.05	-0.06	1.07	-1.08	-1.25	-0.80	-2.42	1.47		
R^2	0.46	0.36	0.51	0.58	0.58	0.54	0.64	0.56	0.59	0.52	0.61	0.41	0.01		
$RMSE$	8.21	8.35	5.99	6.27	7.22	5.94	5.12	5.71	6.16	7.74	5.14	8.03	11.43		

Panel C: Return-on-Assets - Twelve Portfolios

	1	2	3	4	5	6	7	8	9	10	11	12	H-L	F_{GRS}	$p(GRS)$
α_{ALT2}	-0.40	0.29	-0.39	1.04	-0.08	0.68	0.75	0.50	0.96	-0.22	0.28	0.29	0.69	2.210	0.010
β_{MKT}	0.93	0.87	1.11	1.16	1.05	1.00	0.95	1.08	1.08	1.03	0.88	0.83	-0.10		
β_{ROA}	-0.86	-1.06	-0.73	-0.46	-0.01	-0.13	-0.07	-0.02	0.08	0.07	0.08	0.17	1.03		
$t_{\alpha_{ALT2}}$	-0.65	0.52	-0.76	1.73	-0.19	1.90	2.03	1.81	2.39	-0.69	0.75	0.84	1.06		
$t_{\beta_{MKT}}$	7.41	11.46	10.98	10.02	12.41	10.96	11.87	16.80	15.68	16.03	12.17	14.22	-0.84		
$t_{\beta_{ROA}}$	-5.34	-6.63	-4.68	-2.91	-0.08	-1.52	-0.74	-0.50	0.91	1.27	0.94	1.90	6.26		
R^2	0.52	0.63	0.63	0.53	0.52	0.60	0.54	0.71	0.54	0.62	0.53	0.48	0.35		
$RMSE$	9.01	7.70	7.44	8.33	6.57	5.46	5.76	4.49	6.32	5.12	5.21	5.34	9.59		