An alternative approach for investigating risk factors

Using asset turnover levels to understand the investment premiums

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Master Thesis in Finance

December 2016

ABSTRACT

Studying the five-factor asset pricing model developed by Eugene F. Fama and Kenneth R French in 2015, this paper finds conclusive evidence that the premium awarded to non-financial, American firms for exposure towards the newly added investment factor differs depending on firm characteristics. More specifically, a positive relationship is found between the investment risk premium and the asset turnover ratio, a component of the DuPont analysis measuring the asset use efficiency of a firm. Furthermore, the asset turnover ratio is found to be decreasing over time, indicating that the investment factor may become irrelevant when predicting cross-sectional variation in returns going forward. Lastly, an accidental finding proposes that the ratio should be tested as a potential variable for factor construction. The general asset pricing models have been extensively used by both the academic community as well as various capital market participants. Although being able to explain variation in returns for the overall market better than its predecessors, one should be careful when applying the model to predict returns for subgroups of firms. Therefore, this paper suggests moving the research on the subject in an alternative direction.

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Keywords: Asset pricing, Fama and French five-factor model, Investment variable, CMA factor, Asset turnover, DuPont analysis

JEL classifications: C12, C23, G12

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Acknowledgements

We would like to express our deepest gratitude to our tutor Michael Halling, Associate Professor at the Stockholm School of Economics and Research Fellow at the Swedish House of Finance, for his invaluable inputs throughout the process. Furthermore, we would also like to send our regards to Professor Eugene F. Fama, 2013 Nobel laureate in economic sciences and chairman of the Center for Research in Security Prices at Chicago Booth, for taking time to discuss some of the issues in the paper. Thus, we take full responsibility for all shortcomings of this study.

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1. Introduction

The attempt to predict returns is an integral part of the financial economics research field. It attracts the attention of both the academic community and capital market participants such as asset managers and retail investors. Thus, the importance of asset pricing models cannot be understated, as they influence all kinds of financial analysis.

Against the backdrop that a perfect asset pricing model should hold for all assets, much of the focus to date in existing literature has been on developing a single model for predicting variance in all returns.[1] The theory that a one-fits-all model should hold is well explained for early asset pricing models such as the capital asset pricing model (henceforth, CAPM), in which all firms share an exposure towards the market factor. However, most of the later-stage multifactor models that build on the CAPM do not share this theoretical foundation. Factor variables have rather been added in an attempt to explain empirically observed anomalies to the model.

By using the most sophisticated asset pricing model to date, the Fama and French five-factor model published in 2015 (henceforth, the FF-5F model), the purpose of this paper is to show that the investment factor of the model lacks significance when returns are estimated for firms with certain characteristics. This puts forward evidence that the concept of a general multi-factor asset pricing model is inherently flawed, as the investment factor does not systematically explain average returns for some of the investigated subgroups. As a results, this paper will hopefully move the direction of asset pricing research towards understanding the underlying drivers of the input variables, and their applicability in different settings, more thoroughly rather than focusing on finding anomalies.

The research to date on the effect of the level of investments, defined as yearly growth in total assets, on subsequent returns have found a negative correlation between the two. Aharoni, Grundy and Zeng (2013) used a similar regression methodology as the one implemented in this paper to uncover this relationship. By using the definition of Aharoni et al. (2013), Fama and French (2015) construct the investment factor as the difference in returns between firms with low (conservative) and high (aggressive) investments, and conclude that it displays positive average returns. Although this paper observes a similar pattern between investments and returns[2], the study will

[1] An evolution from Markowitz theory in 1952 to the Fama and French five-factor model in 2015, in a continuous effort to improve the predictability of returns.
[2] Table available in Appendix I

deviate from existing literature as it moves from determining the described relationship to understanding the behaviour of it.

Specifically, this paper will analyse the significance of the investment factor in relation to asset turnover, specified as net sales over total assets, which originates from the DuPont equation and is regarded as a measure of a firm's asset use efficiency. For firms perceived as asset use efficient, a change in the asset base should be well received news as it is likely to add sales at a relatively high multiple and, in turn, generate a high return for stakeholders.[3] Therefore, firms with high asset turnovers are expected to be awarded higher premiums for exposures to the investment factor.

The conduct the study, the data is split into subsamples based on levels of asset turnover, and thereafter investigated using a robust two-stage Fama-Macbeth (1973) regression methodology. Moreover, the results are tested for robustness by investigating different portfolios, time periods and returns.

In accordance with the main hypothesis, differences in the significance of the investment factor are found between subsamples of firms, as asset use efficient companies are rewarded a higher risk premium for exposure to the investment factor. In fact, in most cases there seems to be no risk premium awarded at all to asset use inefficient firms.

Furthermore, contrary to popular belief, this study notes that asset turnover levels are decreasing over time. Although difficult to statistically prove that a correlation between the behaviour of the investment factor and the general development of asset turnover exists, it leads the authors of this paper to question the use of the investment factor in future asset pricing models.

These insights highlight the limitations of the FF-5F model and the need for more tailored asset pricing models. As previous research on the subject has been widely implemented in practice, shortcomings of these models have extensive implications for all areas of capital markets, such as fund manager evaluation, investment decisions and project valuation.

The remainder of the paper is structured as follows. Section 2 will present a brief literature review. Section 3 will then discuss the methodology used in the paper, and subsequently, empirical results will be covered in Section 4. Thereafter, Section 5 will put forward the findings and key insight from conducting the study, and lastly, Section 6 will draw conclusions based on the findings.

[3] Ceteris paribus

2. Literature

This section will serve as an introduction to existing research on asset pricing models. Over the years, the study of the predictability of returns has drawn substantial attention in academic literature. Numerous asset pricing models have been developed to better explain variation in returns, several of which have had extensive practical implications as well. In order to truly capture how the asset pricing models have evolved from a single conceptual idea of the risk versus return trade-off, the literature review in subsection 1 will present the previous research in chronological order. Following the literature review, in subsection 2, the rationale for including the investment and profitability factors is explained. Thereafter, in subsection 3, the existing research gap is identified and the hypotheses stated.

2.1 Literature review

In 1952, Markowitz introduced the Modern Portfolio Theory (MPT) based on the concept of the mean-variance efficient frontier and laid the foundation for risk-return theory.[4] His main insight was that investors face a risk versus return trade-off when assessing potential investments. Subsequently, Tobin (1958) found that the investment decision process from the theory developed by Markowitz could be divided into two phases under certain conditions. Firstly, an optimal choice of a combination of risky assets, and secondly, a selection pertaining the allocation of funds between the aforementioned combination of risky assets and a risk-free asset. In equilibrium, the asset prices are set in such a manner that rational investors are able to obtain any point on the capital market line (CML), which is located above the efficient frontier only including risky assets and touches the tangency portfolio. The CML is upwards sloping, indicating that a higher risk level, only considering systematic risk, is associated with higher expected return for an investor.

2.1.1 The capital asset pricing model

The concept of a mean-variance efficient portfolio served as the fundamental idea for the development of the one-factor CAPM by Sharpe (1964), Lintner (1965) and Black (1972). This introduced the market portfolio, which can be

[4] Further developed in 1959 by Markowitz

described as the mean-variance efficient tangency portfolio only invested in risky assets that, combined with risk-free borrowing and lending, is used to generate the set of mean-variance efficient portfolios. In the CAPM developed by Black (1972), there is however no risk-free asset but rather unrestricted short selling of risky assets. The CAPM was developed as an ex-ante model, used to explain the cross-sectional variation in average returns, and includes a risk-free asset and the value-weighted market portfolio. The model is specified as (1):

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM} * \left(R_{Mt} - R_{ft}\right) + \varepsilon_{it} \tag{1}$$

where R_{it} is the return on security or portfolio i for period t, R_{ft} is the risk-free rate, R_{Mt} is the return on the value-weighted market portfolio and ε_{it} is a zero-mean error term. The risk of asset i is measured by β_i, which is the covariance between the return on asset i and the market portfolio divided by the variance of the market portfolio.

Fama and MacBeth (1973) empirically validate the model by performing a two-stage regression method on panel data, which will also be performed in this paper and is further explained in the methodology section. They conclude that the market beta is positively correlated to average returns which indicates that higher risk is associated with higher returns. Furthermore, they also found the relationship between expected returns and risk of a security to be positively linear and lastly, the beta of a security to be a complete measure of risk. The same positive relationship between risk and return had previously been found by Black, Jensen, and Scholes (1972) as well.

The CAPM is still widely used in practice. Graham and Harvey (2001) performed a survey of 392 CFOs, which showed that three quarters are still using the model in their work. However, as an asset pricing model it has come under scrutiny, with numerous empirical caveats presented to its ability to explain returns. Amongst many, Douglas (1969) found that investors are generating returns for taking on other risks not captured in the model and that the estimated relationship between excess returns and betas is too flat. Moreover, the findings of Friend and Blume (1970) and Black, Jensen, and Scholes (1972) indicate that, at least in the period since 1940, the average estimated risk-free rate is systematically greater than the actual risk-free rate and there are additional risk factors not captured by the model. Banz (1981) investigated the size effect on returns and found that average returns are higher for small stocks. Lastly, Stattman (1980), Rosenberg, Reid and Lanstein (1985) and Chan, Hamao and Lakonishok (1991) all found a value effect, defined as book-to-market value of equity, to be significant when explaining returns for both US and Japanese stocks.

2.1.2 The Fama and French three-factor model

In 1993, Fama and French remedied some of the apparent shortcomings of the CAPM model by expanding it into a three-factor asset pricing model. Apart from the market return factor included in the CAPM, the new model incorporated a size factor based on the market capitalisation of firms and a value factor defined as the equity book-to-market ratio (henceforth, this model is referred to as the FF-3F model). The underlying rationale for the two added variables is that they are proxies for common risk factors in returns and that they are related to economic fundamentals. The study, which was performed on the excess returns of 25 portfolios sorted on size and book-to-market equity using NYSE, Amex and NASDAQ stocks for the time period 1963-1990, showed a negative relationship between size and average excess returns as well as a positive relationship between book-to-market equity and average excess returns. The resulting model is depicted as (2):

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM} * \left(R_{Mt} - R_{ft}\right) + s_i * SMB_t + h_i * HML_t + \varepsilon_{it} \tag{2}$$

where R_{it} is the return on security or portfolio i for period t, R_{ft} is the risk-free rate, R_{Mt} is the return on the value-weighted market portfolio, SMB_t is the difference between the returns on diversified portfolios of small and large cap stocks, HML_t is the difference between the returns on diversified portfolios of high B/M stocks (value stocks) and low B/M stocks (growth stocks), and ε_{it} is a zero-mean error term.

The FF-3F model achieved a 90% explanation rate of variation in returns, which was sufficiently higher than the CAPM's explanatory power of 70%.[5] However, the same story applies for the FF-3F model as for its predecessors, with several anomalies being found in subsequent research, indicating that the three factor model does not sufficiently explain the variation in returns. These will not be further delved into in this paper but include

[5] Fama and French (1993)

Sloan (1996) who found a negative relationship between average returns and accounting accruals not priced in by the model. Furthermore, Ikenberry, Lakonishok, and Vermaelan (1995), as well as Loughran and Ritter (1995), showed a negative relationship between average returns and net share issues, Jegadeesh and Titman (1993) documented the existence of a momentum effect, Ang, Hodrick, Xing, and Zhang (2006) found a negative relationship between idiosyncratic volatility and average returns suggesting that the three factor model cannot price portfolios correctly when sorted on this factor, and lastly, Amihud (2002), Pastor and Stambaugh (2003) and Hou, Xue and Zhang (2015a) all found that liquidity risk should be a priced risk factor.

2.1.3 The Fama and French five-factor model

As a response, Fama and French developed the FF-5F model, which augments their previous FF-3F model by incorporating two additional factors. The attempt to improve their earlier work meant adding an investment factor as well as a profitability factor, since previous research indicated that much of the variation in returns that is related to these additional factors is left unexplained by the FF-3F model. The challenge to find appropriate proxies for the underlying profitability and investment variables, used to construct the corresponding factors, have been specified and discussed in previous literature.

Novy-Marx (2013) identifies a proxy for expected profitability as the gross profit divided by total assets, which is found to be related to average future returns. Fama and French (2015) on the other hand define the proxy as current sales minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, all divided by book value of equity. Nonetheless, regardless of definition the rational for the variable is that current profitability is highly correlated with future profitability and should hence be an appropriate proxy for expected profitability.

Aharoni, Grundy and Zeng (2013) defines the investment variable as the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by the total assets at t-2. They found a negative relationship between investments and average returns using a two-stage Fama-Macbeth regression methodology. Additionally, Titman, Wei and Xie (2004) found that firms that substantially increase capital investments subsequently achieve negative benchmark-adjusted returns. Fairfield, Whisenant, and Yohn (2003), as well as findings of Richardson and Sloan (2003), further show that firms that invest more earn lower average returns. These results are consistent with Fama and French's papers from 2006 and 2008, where the investment and profitability variables are discussed.

Fama and French (2015) use NYSE stocks which are sorted into different sets of LHS portfolios. They prove that the FF-5F model produces lower intercepts, and is able to explain a higher degree of the variation in returns, than the FF-3F model, hence it performs better.[6] To test the validity of the asset pricing models, GRS tests developed by Gibbons, Ross and Shanken (1989) are conducted. Fama and French acknowledge in their study that the FF-5F model is rejected using the GRS-test, proving that it is still not a complete model for predicting returns but rather a simplification of reality. Moreover, adding the two additional variables effectively makes the value factor, measured as the book-to-market equity ratio, a redundant factor. In 2015, they also expanded their research by performing their study on international markets and found that their model holds in these markets as well.[7] The model is constructed as (3):

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM} * \left(R_{Mt} - R_{ft}\right) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \varepsilon_{it} \quad (3)$$

where RMW_t is the difference between the returns on diversified portfolios with high (robust) operating profitability and low (weak) operating profitability, and CMA_t is the difference between the returns on diversified portfolios with low growth in total assets (conservative) and high growth in total assets (aggressive).

2.1.4 The DuPont analysis

With the history of asset pricing models thoroughly presented, additional literature relevant to this paper includes the DuPont equation, developed in 1912 by an employee at the public American chemicals company DuPont Corporation. The equation provides a common way of analysing financial statements by decomposing measures of return on capital into different sets of performance indicators for firms. In its simplest form, it decomposes return on assets (henceforth, ROA) into asset turnover, defined as sales divided by the book value of assets, and profit margin, defined as net income divided by sales. This separation of firm performance into subparts of operational efficiency

[6] Fama and French (2015)
[7] Fama and French (2015) International Tests of a Five-Factor Asset Pricing Model

and asset use efficiency often brings a better understanding of the drivers of performance and identifies potential problems for firms. The equation presented (4) will be the focus of this paper but, as previously indicated, it can be adjusted to calculate other sets of financial ratios as well.[8]

$$Return\ on\ assets = \left(\frac{Net\ income}{Sales}\right) * \left(\frac{Sales}{Total\ assets}\right) \tag{4}$$

In previous academic literature, the relationship between earnings and future profitability have been investigated using various financial performance metrics, among them the components that constitute the traditional DuPont analysis. Fairfield and Yohn (2001) found that disaggregating asset turnover and the profit margin is useful when forecasting return on assets one year ahead. Furthermore, Soliman (2008) investigated the use of the DuPont components by market participants. He looked at future forecast errors of year t+1 earnings by examining whether analysts fully understood the implications of the DuPont components in year t on future earnings. Thereby, he found that the DuPont components have predictive power for future forecast errors, suggesting that analysts do not completely utilise the information in these components when issuing their forecasts.

2.2 The rationale for the profitability and investment factors

The rationale of including the profitability and investment factors in asset pricing models stem from the dividend discount model (5) as well as the findings of Modigliani and Miller[9] (6), which, when combined, show the relationship between the factors' underlying variables and the expected return for firms' (7):

$$m_t = \sum_{\tau=1}^{\infty} \frac{E(d_{t+\tau})}{(1+r)^{\tau}} \tag{5}$$

where m_t is the share price at time t, $E(d_{t+\tau})$ is the expected dividends per share at time $t+\tau$ and r is the expected stock return.

[8] Return on assets (ROA), Return on capital employed (ROCE), Return on net operating assets (RNOA) and Return on equity (ROE) are some of the most common performance metrics to study

[9] Miller and Modigliani (1961)

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}} \tag{6}$$

where M_t is the firm value at time t, r is the required return, $Y_{t+\tau}$ is the total equity proceeds at $t+\tau$ and $dB_{t+\tau}$ is the change in the book value of equity from t to $t+\tau$.

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})\,/(1+r)^{\tau}}{B_t} \tag{7}$$

which is a combination of (5) and (6), divided by B_t, which is the book value of equity at time t.

The decomposition in equation (7) shows that expected returns are stipulated by a firm's book-to-market ratio as well as the expectations of future profitability and growth in equity (i.e. investments). Therefore, including these variables in an asset pricing model seems natural and, as discussed in the literature review, it has been a matter of finding appropriate proxies. Variables not directly linked to equation (7), such as size, can add explanatory power by indirectly improving forecasts in the model or capturing horizon effects in the term structure of returns.[10]

2.3 Research gap

Evidently, the existing literature on the subject of asset pricing models is substantial and includes some of the most famous and well-cited papers ever written. However, while the attempts have been numerous to improve the predictability of these models using different sets of variable specifications, with the intent to find a one-fits-all model, this paper aims to instead contribute by offering an alternative route to improve asset pricing models. Specifically, this paper will study the investment factor more thoroughly in an attempt to uncover differences in the predictability of returns between firms as well as over time. By showing that these differences cannot even be reflected in the FF-5F model, the most sophisticated model to date, this paper aims to

[10] Fama and French (2015)

contribute by shifting the focus on the subject in a direction towards creating models more focused on specific subgroups of firms.

Although scarce, there is previous relatable research on the problem of accurately pricing assets when studying sub-samples of data using asset pricing models. Work by Fama and French (1997) and Moerman (2005) have applied asset pricing models to industry-level portfolios. Fama and French (1997) estimate the industry cost of equity using both the CAPM and the FF-3F model on US firms, finding large standard errors due to uncertainty about true risk factor premiums and imprecise risk loadings. Interestingly, the cost of equity for certain industries differs by up to 3% depending on which model is used, and they argue that the cost of equity on a firm-level is even more volatile due to larger variations in true risk factor loadings. This uncertainty is a serious issue for firms as project valuation, impacted by the cost of equity, is essential to the success of a firm. Moerman (2008) on the other hand tests an industry-specific FF-3F model on firms in the euro area. By testing how the FF-3F model performs with factors constructed from general euro-area portfolios compared to factors constructed from industry portfolios, he shows that an industry model performs better and concludes that it might be more appropriate to apply when attempting to understand variation in returns.

The research conducted on the FF-5F model using the aforementioned methodology is limited and to the authors' knowledge, no attempt has been made to identify and understand asset pricing anomalies using the DuPont analysis. In an effort to fill the research gap, this study will therefore test two hypotheses pertaining to an expected relationship between the investment factor from the FF-5F model and the asset turnover variable from the DuPont analysis.

2.3.1 Main hypothesis (H1)

Firstly, the investment factor is expected to be more significant when predicting returns for firms with higher asset use efficiency, which, in line with the DuPont analysis, is defined as asset turnover. The underlying rationale would be that a firm with high asset use efficiency is more likely to convert an investment into sales, and subsequently returns, at a relatively high multiple. This is especially intuitive when investments are defined as growth in total assets, which is the underlying measure of assets used in asset turnover. At this point, one might question the motives for using asset turnover instead of incorporating the profit margin by simply using ROA, which can be considered an obvious measure to study the ability of firms to generate returns from assets. There are three main reasons for why this paper deviates from this metric. First of all, the ROA is more susceptible to financial tampering by firm managers since the net income of a firm is dependent on an almost infinite number of accounting principles. Secondly, the asset turnover is more resistant over time[11] and should therefore be a better estimator of future company characteristics and future returns. Last but not least, the reason for using DuPont in the first place is that it decomposes the performance measure of a firm into more digestible measures that better explain the performance of different aspects of a firm and isolates the underlying drivers of returns. By using asset turnover, the actual efficiency of a firm in the use of its assets is isolated from the profit margin, which is related to the operational efficiency of a firm and not necessarily affected by the assets that a firm employs.

2.3.2 Second hypothesis (H2)

Secondly, as assets have become increasingly productive, the asset use efficiency of firms is expected to have increased, thereby increasing the significance of the investment factor as well. The underlying rationale being that when the productivity of assets increase, the ability to generate sales and the implied returns to investors increase from these assets.

Table 1: Summary of hypotheses

H1	The significance of the investment variable is expected to be positively related to asset turnover levels
H2	Average asset use efficiency is expected to have been increasing over time due to a positive secular trend in asset productivity, and as a result, significance for the investment variable is expected to have increased

[11] Economies of scale makes a high asset turnover ratio difficult to replicate

3. Methodology

This section covers a detailed presentation of the data and the methodology employed in this paper. As the asset pricing model applied does not deviate from the FF-5F model, the methodology section will in many instances be similar. However, differences exists as the data sample differs slightly and the two-stage regression method developed by Fama and Macbeth (1973) is employed to test the FF-5F model.

3.1 Data collection

The full data sample consists of all US companies listed on either NYSE, NASDAQ or Amex. Returns are gathered from the CRSP database while fundamentals are obtained from the COMPUSTAT database. With data assembled from January 1964 to December 2015, it includes individual monthly stock returns for 619 months as well as yearly observations of individual company fundamentals including sales, net income, total assets and common equity for 51 years. As a comparison, Fama and French used US data from June 1963 up to December 2013, which is 18 months shorter than the data sample used in this paper. Additionally, the factor returns for each of the same five factors that were used in Fama and French (2015) are obtained from the database available on Kenneth French's data library.

3.2 Data specification

The data sample used in this paper includes both active as well as inactive US listed companies to avoid a survivorship bias. Furthermore, in order to be able to use the data downloaded from COMPUSTAT and CRSP, the information from the two databases had to be matched using observations of year and ticker as the unique and identifying variables. Subsequently, all observations pertaining to financial services, insurance and real estate companies, with SIC codes of 6000-6799, were deleted from the data. The exclusion of financial firms is in line with common practice. All of the observations with missing values for either total assets or sales were deleted as well, since it is needed to calculate the asset turnover ratio for all companies in order to be able to sort them into different percentiles at a later stage. Lastly, for a security to be included in the regressions at least 24 months of consecutive stock price data leading up to the end of the estimation period needed to be available. After all of these adjustments, a mean of 1,739 companies could be used in the computations for each year, as can be seen in Table (2). Depending on which sorts were used when constructing portfolios out of individual equities, fewer observations were deleted in some cases.[12]

Table 2: Number of firms

	Total sample	Excl. FS, RE and unidentifiable	Final sample
Total	30,512	20,577	8,307
Min	2,189	2,031	321
Max	9,816	7,393	3,097
Mean	6,336	4,534	1,739
Median	7,058	4,488	1,534

Firms included in the total sample are American public firms listed on either NYSE, NASDAQ or Amex and include both active and inactive companies, downloaded from the CRSP. In the second column, all observations pertaining to financial services, insurance and real estate companies, with SIC codes of 6000-6799, as well as observations without SIC codes have been excluded. In the last column, the final sample only includes firms that have fundamental data from COMPUSTAT that could be matched with the stock price data from CRSP. However, there are further deletions in later stages, which are depending on sorts.

3.3 The Fama and French five-factor asset pricing model

In light of the history of asset pricing models, it seems natural to test the hypotheses for the CMA factor on the latest developed model used to explain average returns, namely the FF-5F model. The model has been presented in an earlier section and is depicted as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM} * (R_{Mt} - R_{ft}) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \varepsilon_{it} \tag{1}$$

If the intercept, measured by alpha, is indistinguishable from zero the model fully captures expected returns. Fama and French investigate different variations of the model in their paper to find the lowest possible alpha. However, this paper's primary contribution is to study the behaviour of the CMA factor and how it relates to different levels of asset use efficiency, with the validity of the model being a secondary objective.

3.4 Variable definitions

The variables used in this paper are computed for each individual firm in the full data sample and subsequently used in order to sort individual firms into portfolios. In subsection 1, the different return measures tested are defined

[12] In particular due to a lack of observations for the profitability and investment variables

as well as the risk-free rate. In subsection 2, the defined variables are the same as the variables Fama and French (2015) use to form portfolios when testing their FF-5F model. Thereafter, in subsection 3, the asset turnover variable used specifically in this paper is explained.

3.4.1 Returns

In order to test the empirical results for robustness we use two different return measures in the regressions. For the main tests, total returns from holding a security are used, defined as the change in value of a security including dividends (2). To test for robustness, returns excluding dividends are employed (3).

$$R_t = \frac{V_t + Div_t}{V_{t-1}} - 1 \tag{2}$$

$$R_t = \frac{V_t}{V_{t-1}} - 1 \tag{3}$$

where R_t is the return for the time period *t*, V_t is the value of the asset at time *t*, Div_t is the dividend in time period *t* and V_{t-1} is the value of the asset at time *t-1*.

Similarly to Fama and French (2015), the risk-free interest rate used to obtain the excess returns is the 1-month US Treasury bill rate.

3.4.2 The five-factor asset pricing model

The size variable is defined as the market capitalisation, closing share prices times the number of common shares outstanding, of each individual firm and is calculated at the end of June every year. The rationale for the inclusion of a size variable is its established relationship to average returns. When controlling for the book-to-market ratio in the paper by Fama and French (1993), lower returns are observed for small firms than for big firms.

Market value of equity (henceforth, ME) is calculated in the same manner as the size variable. However, this variable is constructed at the end of year t-1 and is used to obtain the book-to-market ratio in a subsequent stage. Book value of equity (henceforth, BE) is defined as the book value of common equity plus deferred taxes and investment credit less book value of preferred stock, for fiscal year t-1.[13] ME and BE are thereafter used to calculate the book-to-market ratio of each individual firm on a yearly basis (henceforth, B/M). B/M is also related to returns, as Fama and French (1993) show that firms with high B/M (a low share price compared to book value) tend to have lower average returns than firms with low B/M.

The profitability variable (henceforth, OP) is defined as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book value of equity for fiscal year t-1.[14] Basically, it is a measure of how robust or weak this proxy of operating profit is for each individual firm in relation to the book equity of the firm, and it has been shown in the work by Novy-Marx (2013) to be related to average returns.

The final variable used by Fama and French to form portfolios is the investment variable (henceforth, Inv), which is defined as the change in total assets from the end of fiscal year t–2 to the end of fiscal year t–1, divided by total assets at the end of fiscal year t–2. It is a measure of how aggressive or conservative the growth in assets is for each firm in the data sample and serves as a proxy for the investments made by a firm. This variable has been shown by Aharoni et al. (2013) to be related to average returns as well.

3.4.3 The asset turnover variable

In addition to the variables employed by Fama and French, this paper introduces a sorting variable in asset turnover (henceforth, AT), based on fundamental data for each firm gathered on a yearly basis. It is defined as net sales during fiscal year t-1 divided by the total assets at the end of fiscal year t–1 and moreover a common metric used to study the asset use efficiency of firms[15], (henceforth, a complement to using AT). In simpler terms, it is a measure of the net sales that are generated from a unit of total asset.

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[13] Definition from Fama and French (1993)
[14] Definition by Fama and French (2015)
[15] The average of total assets in t-1 and t-2 is commonly used to calculate the asset turnover metric. However, given the resilience of the variable over time as shown in figure (2) in Appendix IV, using the definition of this paper will likely have no impact on the results

3.5 Construction of factors

The right hand side (henceforth, RHS) factor returns used to explain the variance in the excess returns have already been constructed by Fama and French for the US market and are based on the variables presented above. These factor returns are gathered on a monthly basis from Kenneth French's data library for the time period January 1964 to December 2015. The rationales behind the different factors have been explained previously in the literature section. Table (3) below depicts a detailed summary of the construction of factors.

Table 3: Construction of factors

Sorts	Percentile breakpoints	Factor components
2x3 sorts on	Size: 50th	$SMB_{B/M} = \frac{SH+SN+SL}{3} - \frac{BH+BN+BL}{3}$
Size and B/M, or		$SMB_{OP} = \frac{SR+SN+SW}{3} - \frac{BR+BN+BW}{3}$
Size and OP, or		$SMB_{Inv} = \frac{SC+SN+SA}{3} - \frac{BC+BN+BA}{3}$
Size and Inv		$SMB = \frac{SMB_{B/M} + SMB_{OP} + SMB_{Inv}}{3}$
	B/M: 30th and 70th	$HML = \frac{SH+BH}{2} - \frac{SL+BL}{2}$
	OP: 30th and 70th	$RMW = \frac{SR+BR}{2} - \frac{SW+BW}{2}$
	Inv: 30th and 70th	$CMA = \frac{SC+BC}{2} - \frac{SA+BA}{2}$

2x3 independent sorts are obtained from Kenneth French's data library. All formed in June of year t: stocks are assigned two *size* groups and three groups of either book-to-market value (B/M), operating profitability (OP) or investment (INV), depending on which factor that is constructed. Firms are divided into 2 size groups, small (S) and big (B), determined by the median of the firms' market capitalisations. For the remaining variables, stocks are assigned to 3 groups based on the 30th and 70th percentiles for these variables. When assigned on the level of B/M, groups of high (H), neutral (N), and low (L) are created. When assigned on level of OP, groups of robust (R), neutral (N), and weak (W) are created. When assigned on INV, groups of conservative (C), neutral (N), and aggressive (A) are created. The SMB, HML, RMW and CMA factors are then created using the formulas described in the last column.

The summary statistics including mean, standard deviation and t-statistics for the resulting factors are illustrated in table (13) in Appendix I.

3.6 Data split based on the asset turnover variable

Before delving into the method for testing the five factor model, the full data sample is divided into different percentiles based on the levels of AT for each firm. This is to test, at a later stage, whether differences exist between firms with different levels of AT. In choosing the percentiles, the statistical need for a large number of observations had to be balanced with the objective of looking at firms with large differences in AT. Subsequently, this paper will mainly focus on the difference between the 25th and the 75th percentiles to investigate the stated hypotheses, but the 10th and 90th percentiles will also be considered. The percentiles are formed based on the value of AT at the end of fiscal year t-1. The number of firms in each percentile varies over the years, but the average number of firms in each percentile can be found in table (4) presented below. Henceforth, the exact same tests will be performed for all percentiles.

Table 4: Firms in each percentile

	10th	**25th**	**75th**	**90th**
Total	1205	2509	1933	807
Min	32	81	81	32
Max	310	775	775	310
Mean	174	435	435	174
Median	153,5	384	384	153,5

Summary statistics for number of firms in the percentiles investigated. The min, max, mean and median values are for number of yearly observations. Further deletions in later stages, depending on sorts. Percentiles are based on level of asset turnover (AT) at t-1.

3.7 The Fama-Macbeth two-stage regression

In order to test the FF-5F model, and in turn the hypotheses stated in this paper, a two-stage regression methodology first applied by Fama and MacBeth is used.[16] The Fama-MacBeth methodology provides a particularly robust way of empirically testing an estimated premium awarded by investors for an exposure to a particular risk factor.

3.7.1 First-stage regression

The first stage consists of a set of time-series regressions[17] to investigate the exposure of each asset's returns to each risk factor. In general, N time series regressions are performed (where N is the number of assets in the data set), and the regression (4) is the following:

16 Aharoni, Grundy and Zeng (2013) used the same methodology in their asset pricing model test

17 Ordinary least squares (OLS) regressions

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MktRF} * MktRF_t + \beta_{i,SMB} * SMB_t + \beta_{i,HML} * HML_t + \beta_{i,RMW} * RMW_t + \beta_{i,CMA} * CMA_t + \epsilon_{i,t} \tag{4}$$

where the betas are factor loadings to each factor, α_i is the return left unexplained by the model for each firm and $\epsilon_{i,t}$ is the error term.

Since we are investigating such a long period, 1964–2015, the regressions are estimated each year using historical monthly data for the last five years. Hence, each year a new beta is estimated for each asset. The criteria for computing the betas of an asset during year t is that excess returns for the 24 consecutive months leading up to December of year t-1 can be obtained for the particular asset.[18]

3.7.2 Portfolio construction

Prior to performing the second-stage regressions, the individual assets are sorted into different equally-weighted portfolios. However, compared to the original methodology employed by Fama and Macbeth (1973), the portfolios are formed based on fundamental firm data similarly to Fama and French (2015).

The main reason for sorting individual stocks into portfolios is that individual stocks are unlikely to have constant factor loadings over time. Furthermore, sorting individual stocks into portfolios also reduces idiosyncratic volatility. The motivation for creating portfolios is originally stated by Irvin and Blume (1970) who argue that there is an estimation error in betas that is diversified away by aggregating stocks into portfolios. Furthermore, Black, Jensen and Scholes (1972), Fama and MacBeth (1973), and Fama and French (1993, 2015), all apply the same methodology in their asset pricing tests. The literature indicates that more precise estimates of factor loadings will translate into more accurate estimates and lower standard errors of factor risk premia. However, it is important to form the portfolios based on some characteristic that is likely to be correlated with factor returns in order to increase the dispersion between betas of different portfolios and reduce standard errors. Otherwise, the procedure will only lead to a loss of information in the LHS variables.

Several variations of portfolio sorts were considered when analysing how to best capture the variance in excess returns. Starting from the work

[18] This criteria is the same as the one used by Fama and French (1993)

conducted by Fama and French (2015), joint controls should ideally be implemented due to the high correlations between Size, B/M, OP and Inv (the variables used to construct SMB, HML, RMW and CMA) in order to isolate the premium for each factor. The high correlations between risk factors and the Spearman rank correlation between variables for individual firms are illustrated below in tables (5) and (6). A 2x2x2x2 sort related to Size, B/M, OP, and Inv have been tested to control for all variables included in the regression. However, since multivariate regression slopes measure marginal effects, the ability of the 2x2x2x2 sort to better isolate exposures to variation in returns is still not obvious. Due to the ambiguity of the reasoning behind different portfolio sorts, a wide set of portfolio sorts is tested.[19] This is to investigate whether the empirical results are robust or dependent on the sorts chosen.

Table 5: Factor correlation matrix

	MktRF	SMB	HML	RMW	CMA
MktRF	1				
SMB	0.2732	1			
HML	-0.2643	-0.0891	1		
RMW	-0.2326	-0.3520	0.0742	1	
CMA	-0.3880	-0.1085	0.6917	-0.0360	1

Table 6: Spearman rank correlation between variables

	Size	B/M	OP	Inv
Size	1.0000			
B/M	-0.3795	1.0000		
OP	0.3197	-0.1800	1.0000	
Inv	0.1440	-0.1731	0.2346	1.0000

Regarding the time of sorting, this paper follows the same procedure as Fama and French (2015). For the size variable, portfolios are formed based on Size ranking at the end of June at calendar year t-1 for each year t. For the value variable, the B/M of each year t is obtained by dividing the BE at the end of fiscal year t-1 by the ME at the end of year t-1. Similarly, both the OP and INV variables for year t are computed at the end of the fiscal year t-1. Portfolios are hence sorted before the testing period, t. This is done in order to be able to test the true predictive power of the model. See table (7) for details.

[19] Similarly to Fama and French (2015)

Table 7: Portfolio formation, estimation and testing periods

	Period
Testing period	t
Portfolio formation period	t-1
End of estimation period	t-1
Beginning of estimation period	t-5
Minimum required beginning of estimation period	t-2

An important distinction from the work of Fama and French (2015) is that the data is sorted sequentially rather than independently. In their study of hedge fund returns, Agarwal et al. (2008) perform a conditional three stage sort as they argue that the risk premiums are contaminated by cross-sectional effects due to high levels of rank correlations between the sorting variables. Given the above, sorting portfolios independently poorly captures risk premiums, which would indicate that the methodology of Fama and French (2015) is not appropriate. Furthermore, sorting independently when high correlations between rankings are present could lead to an unbalanced set of portfolios, with a few portfolios representing the majority of the companies. The Spearman rank correlations between the sorting variables in the data sample, shown previously in table (6), provide further evidence that a sequential procedure for sorting the portfolios is preferred in order to obtain pure estimates of the returns associated with each risk exposure.

Table 8: Portfolio construction

Sorts	Breakpoints
5x5 sort on Size and B/M	Quintiles
5x5 sort on Size and Inv	Quintiles
2x3x3 sort on Size, B/M and Inv	Median and tertiles
2x4x4 sort on Size, OP and Inv	Median and quartiles
2x2x2x2 sort on Size,B/M, OP and Inv	Medians

Portfolios are constructed on the data sample based on non-financial American firms obtained from CRSP and COMPUSTAT databases. The different varieties of portfolio sorts are based on different combinations of *size*, book-to-market value ratio (*B/M)*, operating profitability (*OP)* and investment *(INV)*. Portfolios are formed in June of year t for size and fiscal year t-1 for the remaining variables. Sequential sorts are applied with the first sort on the Size variable followed by variations of BE/ME, OP and INV variables using median, tertiles, quartiles and quintiles breakpoints for different variations of portfolio sorts.

Lastly, the portfolios are resorted in the beginning of each year in order to allow for variations in company fundamentals from year to year. This approach creates more dynamic portfolios that represent the market better for each year, compared to the portfolios in Fama and Macbeth (1973) that are resorted every fifth year. Furthermore, it increases the sample size, since new firms can enter the portfolios each year. Table (8) shown below summarises the variations of sorts implemented.

3.7.3 Second-stage regression

After portfolio sorts have been conducted, second-stage regressions[20] can be performed for each set of portfolio sorts. Although the assets' exposures are obtained from running the first stage regressions, second stage regressions are needed to investigate the risk premium rewarded for a unit exposure to each factor. The second stage involves a cross-sectional regression for each month considered in this paper. The second stage regression model (5) is depicted as:

$$R_{p,t} - R_{f,t} = \gamma_{0,t} + \gamma_{MktRF,t} * \hat{\beta}_{MktRF,t-1} + \gamma_{SMB,t} * \hat{\beta}_{SMB,t-1} + \gamma_{HML,t} * \hat{\beta}_{HML,t-1} + \gamma_{RMW,t} * \hat{\beta}_{RMW,t-1} + \gamma_{CMA,t} * \hat{\beta}_{CMA,t-1} + \eta_{p,t} \tag{5}$$

where $\gamma_{1,t}$ are regression coefficients that capture the risk premium awarded in month *t* for a unit exposure to the corresponding factor. As mentioned, this cross-sectional regression is performed once for each month *t*.

In a last step, the estimated second-stage regression coefficients are averaged over the total time period (January 1968[21] to December 2015) in order to obtain an estimated risk premium for each factor. The average coefficients represent the risk premium awarded for a unit factor exposure over time. Treating each observation of γ as an independent observation and identically distributed (i.i.d.), the standard error can be calculated. Thereafter, a t-statistic can be calculated to test whether the γ for each factor is different from zero. The t-statistic (6) is calculated as:

[20] Huber-White sandwich estimators are used

[21] The first five years of data, January 1964-December 1967, are only used to estimate betas

$$\frac{\bar{\hat{\gamma}}_j}{s(\hat{\gamma}_j)/\sqrt{T}} \tag{6}$$

where $\bar{\hat{\gamma}}_j$ is the average of monthly estimated regression coefficients of factor j, $s(\hat{\gamma}_j)$ is the standard deviation of $\hat{\gamma}_j$ and T is the total time periods in number of months.

4. Empirical results

In this section, the empirical results are presented and analysed. For complete transparency and to show the robustness in the findings of this paper, several variations of the results are displayed. First, a brief description of the data, on individual firm level, in our sample is presented. Second, the results of the two-stage Fama-Macbeth regressions are illustrated. Due to the multitude of similar results, the analysis will focus on one of the portfolio sorts when presenting the portfolio data and the second-stage regression results. Finally, the robustness of the results is discussed and the limitations are presented.

4.1 Data description and factor validation

4.1.1 Data

The data sample consists of 83,332 monthly observations of firm level data. Table (9) below describes summary statistics of these observations. The statistics are presented for all firms regardless of percentile belonging, which creates a wide spread in the values of the *Asset turnover* variable, ranging from -0.221 to 227.449. The negative AT ratios observed are due to negative net sales numbers, which is not an error in the data set but rather a result of the use of accounting principles.

Moreover, the mean value of the variable *year*, which indicates the year an observation belongs to, illustrates that the data is unevenly distributed throughout the time period considered. This is due to the fact that there are more public companies in the US today than there were in 1968. Despite not creating problems for the regressions, it is worth mentioning that most of the observations are in the later part of the data.

Additionally, the number of observations of each variable is lower for *OP* and *Inv* than for the rest of the variables. As a result, when sorting individual securities into portfolios based in part on either *OP* or *Inv*, some observations cannot be used.

Table 9: Summary statistics of sorting variables

Variable	Mean	Std. Dev.	Min	Max	N
$year$	1,998.813	11.736	1,968.000	2,015.000	83,332
$Asset\ turnover$	1.157	1.904	-0.221	227.449	83,332
$Mkt\ cap$	2,863,344	147,479,46	25	715,599,808	83,332
B/M	0.004	0.072	-0.663	6.016	83,266
OP	0.620	58.966	-731.750	9,423.750	78,002
Inv	0.553	62.894	-1.000	15,509.000	75,029

Summary statistics for the variables used to sort the data sample based on non-financial American firms obtained from CRSP and COMPUSTAT databases. It includes mean, standard deviation, minimum, maximum and number of firm-year observations for each variable. All data is on firm level, not portfolio level. The variable *year* is the fiscal years between the time period January 1968 to December 2015. Asset turnover (*AT*) is defined as net sales during fiscal year t-1 divided by the total assets at the end of fiscal year t−1. The *size* variable is defined as the market capitalisation ($mkt\ cap$) and is calculated at the end of June every year. B/M is defined as the market value of equity (mkt cap) divided by the book value of equity at the end of year t-1. *OP* is defined as the annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book value of equity for fiscal year t-1. *Inv* is defined as the change in total assets from the end of fiscal year t−2 to the end of fiscal year t−1, divided by total assets at the end of fiscal year t−2.

4.1.2 Validation of the investment factor

Presented in table (13) in Appendix I are the average excess returns for each relevant AT percentile for portfolios formed on *Size*, *B/M* and *Inv*. Evidently, the negative relationship found in previous literature showing that firms that invest aggressively experience lower subsequent returns, is observable in these data samples as well. Thus, prior to delving into the main findings of this study, the investment factor has effectively been validated within the data.

4.2 Evaluation of results

4.2.1 First-stage regressions

Table (10) depicted below summarises the results of the first-stage regressions. These are the same regardless of portfolio sort, except for when sorting on *OP* or *Inv* in which case there are fewer observations but with similar outcome. Similarly to the summary statistics for the sorting variables, there is a wide spread in the results because the first-stage regressions are performed and presented on an individual firm level. However, even though the results vary substantially between firms and years, the average results are intuitive. For instance, the market beta, β_{MktRF}, is close to 1 and the alpha, α, is close to 0.

$$R_{i,t} = \alpha_i + \beta_{i,MktRF} * MktRF_t + \beta_{i,SMB} * SMB_t + \beta_{i,HML} * HML_t + \beta_{i,RMW} * RMW_t + \beta_{i,CMA} * CMA_t + \epsilon_{i,t}$$

Table 10: Summary of first-stage regression results

Estimate	Mean	Std. Dev.	Min	Max	N
β_{MktRF}	1.008	0.827	-13.047	22.240	
β_{SMB}	0.769	1.169	-19.897	34.526	
β_{HML}	0.024	1.521	-58.785	25.872	83,332
β_{RMW}	-0.242	1.918	-59.748	43.637	
β_{CMA}	-0.073	2.189	-46.236	96.227	
α	0.006	0.025	-0.206	0.541	

Summary statistics for the firm-level first-stage time-series Fama-MacBeth (1973) regression methodology to obtain exposure towards each factor in the FF-5F model. The results are from OLS regressions. The data sample consists of 83,332 firm-year observations for the time period January 1968 to December 2015 and is based on non-financial American firms obtained from CRSP and COMPUSTAT databases. All data on firm level, not portfolio level.

4.2.2 Second-stage regressions

Prior to performing the second-stage regressions the data is divided into different percentiles based on AT, and the individual securities are combined to form equal weighted portfolios based on different sorts. When analysing the results of the second stage regressions, the 2x3x3 sort on *Size*, *B/M* and *Inv* will be used.[22] There are two reasons for focusing on this particular portfolio sort. First, all of the sorts produce similar results and second, the results from the 2x3x3 sort are the most pronounced.

In the second-stage, the input variables are the results from the first-stage regressions subsequent to sorting the individual securities into portfolios. The summary statistics for these are presented for each percentile in table (11) below.

The first interesting finding is that the standard deviations of all betas are considerably lower than those of the betas previously presented in table (10), and there are much lower spreads between minimum and maximum values. This is an effect of sorting the individual securities into portfolios, as it diversifies away idiosyncratic volatilities and lowers dispersion in betas, at the risk of losing information.

A second observation worth mentioning is that average portfolio returns are increasing with each percentile. This is evident in table (13) in

[22] Hou, Xue and Zhang (2012) used the sort in their paper

Appendix I as well, where one can observe that even individual portfolio returns are considerably higher in the percentiles with high AT. Although possibly a coincidence, and outside of the scope of this paper, it might be because the AT variable used to sort firms into different percentiles is constructed similarly to, and probably correlated with, the profitability variable. This theory is supported by the fact that the average exposure to RMW, β_{RMW}, increases with each percentile as well. This accidental finding is intriguing in itself since Fama and French (2015) could not fundamentally justify the behaviour of the exposure to the RMW factor for the portfolios in which the FF-5F model failed to accurately estimate returns. The finding is therefore an important indication that the AT variable could potentially be used to construct a factor to replace the RMW.[23]

[23] Note here that the definition of profitability by Novy-Marx (2013), gross profits divided by assets, is even closer to asset turnover

Table 11: Second-stage regression input variables (2x3x3 sort)

Variable	Mean	Std. Dev.	Min	Max	N
			10th Percentile		
R_p	0.00841	0.09221	-0.38634	1.66218	9,936
β_{MktRF}	0.96538	0.35096	-0.36268	3.32676	
β_{SMB}	0.71154	0.64199	-1.16103	4.29624	
β_{HML}	-0.05421	0.70917	-2.70606	2.98365	
β_{RMW}	-0.68152	0.89425	-5.38181	4.03922	
β_{CMA}	0.01919	1.04275	-4.14513	5.35227	
			25th Percentile		
R_p	0.00928	0.07128	-0.37453	0.73995	9,936
β_{MktRF}	0.97111	0.23001	0.21674	1.91104	
β_{SMB}	0.65213	0.50018	-0.57218	2.73596	
β_{HML}	-0.03589	0.48013	-2.29109	1.86866	
β_{RMW}	-0.44998	0.56588	-3.14780	0.98609	
β_{CMA}	0.02393	0.63931	-2.98154	2.68391	
			75th Percentile		
R_p	0.01189	0.06831	-0.32080	0.64407	9,936
β_{MktRF}	0.94918	0.21898	0.03056	2.24654	
β_{SMB}	0.90187	0.37084	-0.31377	2.17820	
β_{HML}	0.12579	0.43633	-1.52825	3.24637	
β_{RMW}	0.03785	0.49844	-1.66146	1.59735	
β_{CMA}	0.02674	0.56612	-2.54674	2.20952	
			90th Percentile		
R_p	0.01265	0.08060	-0.38587	1.08394	9,936
β_{MktRF}	0.93420	0.29410	-0.32341	1.96980	
β_{SMB}	0.90811	0.48931	-0.71496	3.38093	
β_{HML}	0.09585	0.60845	-2.52534	4.17947	
β_{RMW}	0.05942	0.73834	-3.04934	3.27258	
β_{CMA}	0.01906	0.79229	-3.04615	4.76808	

Summary statistics for second-stage regression using the Fama-MacBeth (1973) regression methodology, which investigate the risk premium rewarded for a unit exposure to each factor. The results are from cross-sectional regressions for each month in the data sample, using Huber-White sandwich estimators. Firms in the data sample include non-financial American firms obtained from the CRSP and COMPUSTAT databases, from January 1968 to December 2015. Firms are assigned to percentiles based on yearly level of asset turnover (*AT*) in t-1. All data is on portfolio level. (R_p) is the equal weighted return for each portfolio considered within the investigated percentiles. Thereafter, summary statistics for factor premiums, in order, for the market factor (*MktRF*), size factor (*SMB*), value factor (*HML*), profitability factor (*RMW*) and investment factor (*CMA*) are obtained.

As explained in the methodology section, the main reason for creating portfolios is that it reduces estimation errors in betas since they are diversified away. By the same logic, this paper starts off by comparing the 25th percentile to the 75th percentile. These percentiles contain the largest number of underlying firms and the diversification effect from creating portfolios should hence be greater in these percentiles than in the 10th and 90th percentiles, resulting in the most accurate results. Results for the second stage regressions using the full sample period are displayed below in table (12) for the 25th percentile and the 75th percentile.[24] For results on other percentiles, portfolio sorts, time periods and return definitions, less detailed summaries are available in Appendix II.[25]

$$R_{p,t} = \gamma_{0,t} + \gamma_{MktRF,t} * \hat{\beta}_{MktRF,t-1} + \gamma_{SMB,t} * \hat{\beta}_{SMB,t-1} + \gamma_{HML,t} * \hat{\beta}_{HML,t-1} + \gamma_{RMW,t} * \hat{\beta}_{RMW,t-1} + \gamma_{CMA,t} * \hat{\beta}_{CMA,t-1} + \eta_{p,t}$$

Table 12: Second stage regression output, 1968-2015 (2x3x3 sort)

$Factor\ (f)$	$\bar{\hat{\gamma}}_f$	$s(\hat{\gamma}_f)$	$t(\bar{\hat{\gamma}}_f)$	$p(\bar{\hat{\gamma}}_f)$
		25th Percentile		
$MktRF$	-0.00283	0.07069	-0.94128	0.34697
SMB	0.00559	0.04468	2.94157	0.00340
HML	0.00521	0.04608	2.65420	0.00818
RMW	-0.00257	0.03504	-1.72260	0.08552
CMA	0.00230	0.03374	1.60361	0.10937
0	0.00820	0.07161	2.68953	0.00737
r^2		0.46820		
$s(r^2)$		0.19708		
		75th Percentile		
$MktRF$	-0.00023	0.072208	-0.07368	0.94129
SMB	0.00489	0.05305	2.16347	0.03093
HML	0.00601	0.04556	3.09890	0.00204
RMW	-0.00131	0.03497	-0.88168	0.37833
CMA	0.00348	0.03247	2.51931	0.01204
0	0.00650	0.07117	2.14666	0.03226
r^2		0.40264		
$s(r^2)$		0.17927		

Results obtained for the second-stage Fama-MacBeth (1973) regression methodology, which investigate the risk premium rewarded for a unit exposure to each factor. Firms in the data sample include non-financial American firms obtained from the CRSP and COMPUSTAT databases, for the period January 1968 to December 2015. Firms are assigned to percentiles based on yearly level of asset turnover (*AT*) in t-1, with these results only including the 25th and 75th percentile. All data is on portfolio level. The results are from cross-sectional regressions for each month in the data sample, using Huber-White sandwich estimators. The average gamma for each factor, followed by the corresponding standard error as well as t-statistics and p-value is presented for the market factor (*MktRF*), size factor (*SMB*), value factor (*HML*), profitability factor (*RMW*), investment factor (*CMA*) as well as the constant ($gamma_0$). Moreover, the overall model fit determined by the r-square is presented for both percentiles based on the yearly level of asset turnover (*AT*) with the corresponding standard error for the r-square.

[24] Detailed results are available in Appendix III
[25] In total, 80 individual results on the CMA factor from running different regression variations are available

Starting from a general perspective, the second stage regressions produce average values of r^2 which must be considered satisfactory for this type of regression. For comparative purposes, one can relate this to Fama and Macbeth (1973), who received an $\overline{r^2}$ value of 0.29 when performing the second stage regressions on their full sample period using the exposure to the market risk premium as the only explanatory variable.

Furthermore, the r^2 is higher in the 25th percentile than in the 75th percentile, which might be surprising if one expects the CMA factor to be irrelevant when explaining returns in the 25th percentile as it contains firms that are less efficient in their use of asset. However, the difference is not very large and could be down to a number of reasons unrelated to the CMA factor, hence this paper will not discuss this further.

4.2.3 Evaluation of the main hypothesis

To evaluate the main hypotheses (H1) regarding the significance of the CMA factor, focus should be on the t-statistic, $t(\bar{\hat{\gamma}}_{CMA})$, which tests the null hypothesis that $\bar{\gamma}_{CMA} = 0$. If the null hypothesis can be rejected, one should be able to conclude that the CMA factor is significant when estimating returns in the corresponding data sample.

In this case, the empirical results could be considered clear. In the 75th percentile, the t-statistic for $\bar{\hat{\gamma}}_{CMA}$ is 2.519, whilst the corresponding t-statistic in the 25th percentile is 1.604. This effectively means that the null hypothesis can be rejected at a 5% level in the 75th percentile, but cannot even be rejected at a 10% level in the 25th percentile.[26] Therefore, the empirical evidence suggests that the CMA factor is indeed significant in the higher percentiles containing more asset use efficient companies, but cannot with statistical significance be used in the FF-5F model to predict returns for inefficient ones. Thus, H1 holds in this case.

Using the same portfolio sort to compare the 10th and 90th AT percentiles produces the same results, which further strengthens the interpretation that H1 holds. In the 10th percentile, the t-statistic for $\bar{\hat{\gamma}}_{CMA}$ is 0.844 and the factor is therefore insignificant. At the same time, a t-statistic of 1.994 is observed in the 90th percentile, again showing that the null hypothesis can be rejected at a 5% significance level. When analysing the results in the

[26] Under the assumptions of a student's t-test

deciles however, the results should be taken more lightly since there is a greater chance that the results are found by chance and that they are in fact an anomaly.[27] Supportive of this are the t-statistics found for MktRF, HML and RMW, which are insignificant in both the 10^{th} and 90^{th} percentile, HML being just insignificant with $t(\bar{\hat{\gamma}}_{HML}) = 1.57$. The fact that so many factors are insiginificant in the 10^{th} and 90^{th} percentiles suggests that the use of portfolios, which contained a smaller amount of companies as a result of using smaller percentiles, did not properly diversify away the estimation errors in betas in some cases. However, the fact that the CMA and SMB factors still are significant either provides strong evidence for the relevance of these variables or an anomaly. This will be investigated further in the subsequent robustness section.

Furthermore, although one should be careful when drawing conclusions based on this, the values of $\bar{\hat{\gamma}}_{CMA}$ are higher in the 75^{th} and 90^{th} percentiles than in the 25^{th} and 10^{th} percentiles, which indicates that a unit exposure to β_{CMA} is given a higher premium in the higher percentiles than in the lower percentiles. This is not statistically proven, since neither a t-test to see if $\bar{\hat{\gamma}}_{CMA,25th} = \bar{\hat{\gamma}}_{CMA,75th}$, nor a t-test to see if $\bar{\hat{\gamma}}_{CMA,10th} = \bar{\hat{\gamma}}_{CMA,90th}$, can be rejected even at a 10% level. However, there is one more statistic that can be analysed, which is $t(\bar{\hat{\gamma}}_{CMA} = \overline{CMA})$ for each percentile. The results of this test should be studied moderately since there are many unknown variables in the two-stage regression, but it can still give a relevant indication since it must hold in order for the FF-5F model to be valid, if each beta is estimated correctly on average.[28] The explanation is presented below.

Given the estimated equation:

$$R_{p,t} - R_{f,t} = \hat{\gamma}_{0,t} + \hat{\gamma}_{MktRF,t} * \hat{\beta}_{MktRF,t-1} + \hat{\gamma}_{SMB,t} * \hat{\beta}_{SMB,t-1} + \hat{\gamma}_{HML,t} * \hat{\beta}_{HML,t-1} + \hat{\gamma}_{RMW,t} * \hat{\beta}_{RMW,t-1} + \hat{\gamma}_{CMA,t} * \hat{\beta}_{CMA,t-1} + \hat{\eta}_{p,t}$$

[27] Email correspondence with Professor Eugene F. Fama
[28] The underlying rationale of the test pertains to a similar test being conducted by Fama-MacBeth (1973)

And that under the OLS constraint:

$$\sum_{p} \hat{\eta}_{p,t} = 0$$

If:

$$\bar{\hat{\beta}}_{MktRF,t-1} = \bar{\beta}_{MktRF,t-1};\ \bar{\hat{\beta}}_{SMB,t-1} = \bar{\beta}_{SMB,t-1};\ \bar{\hat{\beta}}_{HML,t-1} = \bar{\beta}_{HML,t-1};\ \bar{\hat{\beta}}_{RMW,t-1} = \bar{\beta}_{RMW,t-1};\ \bar{\hat{\beta}}_{CMA,t-1} = \bar{\beta}_{CMA,t-1}$$

Then the following must hold for the model to be valid and the CMA factor to be correctly specified:

$$\bar{\hat{\gamma}}_{CMA} = \overline{CMA}$$

Using t-tests, this cannot be rejected at the 10% level for any of the percentiles. However, the t-statistics for the samples with lower asset use efficiency display larger absolute t-statistics, especially for the 10th percentile, which is -1.44091. As mentioned earlier however, the test is too imprecise for conclusions to be drawn from this finding.

To conclude, when using the 2x3x3 sort, this paper finds the CMA factor to be significant in the data samples containing asset use efficient firms, but not in the data samples containing inefficient firms. Thus, the main hypothesis H1 cannot be rejected. The results are intuitive since companies with high asset use efficiency can be considered more likely to turn their investments in assets into sales and thereby, return capital to investors. To further confirm the main hypothesis, variations of the regression will be presented in the robustness section.

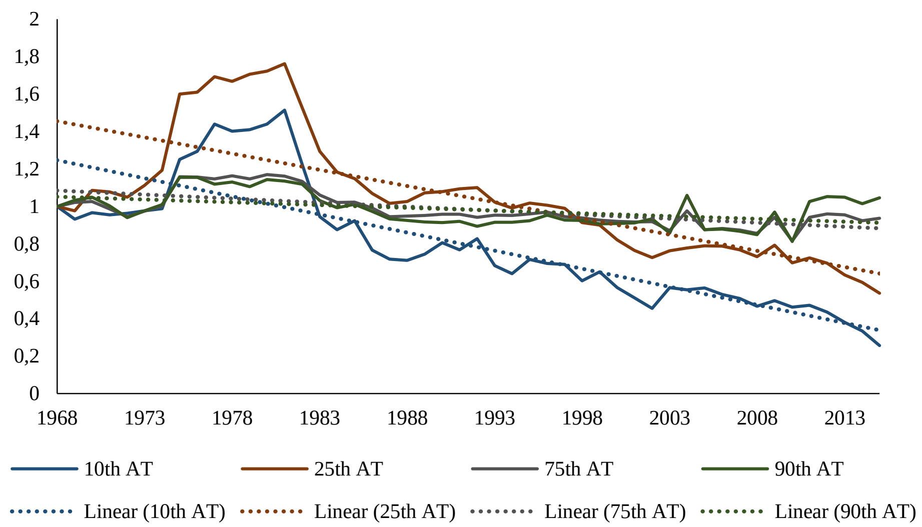
4.2.4 Evaluation of the second hypothesis

When evaluating the second hypothesis (H2), the trend for asset use efficiency is first analysed to see whether the initial expectation regarding the development of the variable is correct. After that, the second-stage regressions are once again performed, only this time on the second half of the data samples, post

1990.[29] These results are then evaluated in relation to the trend for asset use efficiency and also compared to the second-stage regression results for the full period.

First of all, the trend for asset use efficiency is clearly not the expected one. As can be seen in figure (2) in Appendix IV, it is significantly negative for the overall market. With this new information at hand, an initial expectation would not have been that the CMA factor have become more significant over time, but rather the opposite. As the average asset use efficiency decreases, the importance of growth in assets should follow since the assets are not able to relatively generate the same amount of sales and, in turn, returns for the stakeholders of the firms. To further investigate how this is related to the data samples of this study, the asset use efficiency in the investigated percentiles must be considered, which is displayed in figure (1) below. For illustrative purposes and to ease comparisons between percentiles, all values have been rebased to 1968.

Figure 1: Asset turnover (*AT*) development (1968 to 2015)



The figure illustrates the annual asset turnover levels between January 1968 and December 2015 for both active and inactive non-financial, American firms included in the Fama-Macbeth regressions. Asset turnover is defined as yearly sales in t divided by total assets in t. The data set is split into the asset turnover percentiles specifically considered in this paper.

As can be seen, all percentiles display negative slopes for asset use efficiency. Why this is the case is an interesting topic in itself and a brief discussion about it, and the possible implications it might have, will

[29] For robustness but not shown in the results of this paper, the time periods 1985-2015 and 1995-2015 have also been tested

follow in the discussion section. The aim of this paper is to find if, and understand how, this affects the significance of the CMA factor when predicting returns. Interestingly, the asset use efficiency for the lower percentiles have decreased at a much quicker rate than for the top percentiles. In the top percentiles, slightly negative trends are observed, even though the current asset use efficiency in the 90th percentile is in fact higher than it was in 1968. If the expected relationship between asset use efficiency and the significance of the CMA factor holds, one would hence expect that the CMA factor might still be a relevant variable when estimating returns in the top percentiles. For the lower percentiles though, the CMA factor is expected to show no significance given this new information.

To further investigate the H2 and see if a relationship between the decreasing asset use efficiency and the differences in the CMA factor over time is present, the second stage regressions are performed on the second half of the data sample, post 1990. The results are presented in Appendix II. As can be seen, the t-statistics for the null hypothesis that $CMA = 0$ indicate that the CMA factor is insignificant at a 10% level in all samples except for the 90th, where $t(\bar{\hat{\gamma}}_{CMA}) = 1.867$. Note here that the problem of diversifying away estimation errors in betas for the 10th and 90th percentiles should not be as large in this sub-period, since the amount of firms is much larger in the second half of the sample. Therefore, the estimated t-statistic for the 90th percentile can be considered reliable in this case. Furthermore, the fact that the CMA factor is significant for the 90th percentile in this sub-period further strengthens the evidence that the CMA factor was significant for the 90th percentile in the full period.

It should also be noted that for the 75th percentile the t-statistic is at 1.485, which is considerably higher than the t-statistic for the lower percentiles. In the case of the 75th percentile, the lower t-statistic can partly be attributed to the shorter time period. The estimated $\bar{\hat{\gamma}}_{CMA}$ and $s(\hat{\gamma}_{CMA})$ are similar to the ones that were estimated for the 90th percentile in the full sample, the only difference being that the number of observations is smaller.[30] Additionally, a similar pattern in the drop of the t-statistics when considering a shorter time period is observed for the remaining factors as well, indicating that the problems of finding significance do stem from fewer observations.

[30] Fama and Macbeth (1973) also experience problems finding significance for the risk premium they estimated for exposures to the market factor when investigating shorter time periods

When observing the t-statistics for $\bar{\gamma}_{CMA} = \overline{CMA}$, for which the reasoning was explained previously, no extreme values are found. All values can be considered too close to 0 to reveal anything new, given the uncertainty of the test. It will hopefully be more relevant when performing the tests for robustness in the next part, where more values for the statistic will be calculated with the hope that a pattern will appear.

Nonetheless, the data supports a relationship between the significance of the CMA factor and the development of asset use efficiency over time. H2 was rejected due to the fact that the development of asset use efficiency had an opposite sign to the one expected. However, the positive relationship expected between the development of asset use efficiency and the significance of the CMA factor still holds, since the significance of CMA has decreased. To see if the results are truly robust or just due to an anomaly found due to the low number of monthly observations in the second half of the period, several robustness checks must be conducted. This will be delved into in the next section.

4.3 Robustness

To test the results regarding H1 and H2 for robustness, the regression methodology is performed with several variations. First of all, five different portfolio sorts are used in order to ensure that the results found are not simply an anomaly due to the choice of portfolio sort. Secondly, the traditional definition of returns is exchanged for returns excluding dividends in order to see if the results are persistent.[31] Last but not least, the time period is varied between the full period and the late period in order to see if the changes observed over time are robust. Altogether, the first- and second-stage regressions are performed in 20 different versions for each percentile. The results of these regressions are presented in Appendix II. To conserve space, the available estimates have been limited to the ones relevant when analysing the CMA factor and the ones that illustrate the validity of the full model.[32] To make the results comparable between sorts and percentiles, the results are separated into different tables depending on the time period considered and the choice of return definition.

[31] For instance, Schwert's (1990) study on US stock indices looks at daily returns including- and excluding dividends

[32] More detailed results for the main portfolio sort is available in Appendix III

To begin with, the predictive power of the model is relatively resilient through all percentiles, sorts, time periods and return definitions. The values of $\overline{r^2}$ ranges from 0.228 and 0.525, with most of the values being above 0.3. As shown previously in table (12), one can identify a clear and consistent pattern of higher values for the lower percentiles than the higher percentiles, showing that the model has greater predictive power for firms with low asset use efficiency. This pattern is observable for the values of $s(r^2)$ as well. Again, these findings will not be delved into further, however, it could be an interesting topic for future research. At this point, it is more relevant to simply identify that the full model has predictive power in all percentiles.

Studying the $\overline{\hat{\gamma}}_0$ for the different regression variations, it is possible to determine which model specifications that leave the least variation in returns unexplained. Contrary to the case with the $\overline{r^2}$, there is no clear cut pattern observed in the results when the percentiles are compared with each other. However, when it comes to the t-statistics of $\overline{\hat{\gamma}}_0$, a conclusion can be drawn. In almost all cases, the t-statistics are statistically different from zero at a 5% significance level, indicating that the model is not a complete model for estimating variation in returns.[33] The cases whereby the $\overline{\hat{\gamma}}_0$ is not significantly different from zero pertain to the results from the 90th percentile, for which one should be careful drawing conclusions as the number of observations is smaller thereby distorting the results as discussed previously.

Moving on to the factor of focus, CMA, it is interesting to see that the average values for gamma are generally higher for the asset use efficient companies than for the inefficient ones. This is especially true when comparing the 75th percentile to the 25th. $\overline{\hat{\gamma}}_{CMA}$ is higher in the 75th percentile at all times except for when using the 2x4x4 sort on the full sample period. In other words, the 75th percentile displays higher values in 90% of the cases studied. The opposite holds for $s(\hat{\gamma}_{CMA})$, which is, with a few exceptions, lower for the firms with high asset use efficiency.

Even though it has not been statistically tested, it is also interesting to see that the average value for all estimated $\overline{\hat{\gamma}}_{CMA}$ in the 75th percentile follows the average value of CMA closely through the tested periods, independent of return definition, suggesting that the factor holds up well in the sample.

[33] A similar conclusion was drawn by Fama and French (2015) when investigating their FF-5F model

The consistent high values of $\overline{\hat{\gamma}}_{CMA}$, and low values of $s(\hat{\gamma}_{CMA})$, result in higher values of $t(\overline{\hat{\gamma}}_{CMA} = 0)$ for almost all regression estimations in the top percentiles. In the full period for the 75th percentile, the null hypothesis can be rejected at a 5% level regardless of sort and return definition, which illustrates the robustness of the significance for the CMA factor in that sample. Even though the CMA factor is not significant in all cases when analyzing the 75th percentile post 1990, the t-statistics are still greater in the 75th percentile than in the 25th, regardless of sort and return definition. It must be mentioned here also that the average CMA is lower during 1990-2015 while the standard deviation is the same, which would make it more difficult to detect a statistically significant average of $\hat{\gamma}_{CMA}$ even if the true $\bar{\gamma}_{CMA} = CMA$.

All of the above is supportive of H1 which can be concluded to hold when comparing the 25th and 75th percentiles to each other, and when comparing the 10th percentile to the 90th percentile the values are once again indicating that H1 is robust. The t-statistics for the 10th percentile is insignificant at a 10% level in all tests performed. At the same time the CMA factor is significant in the 90th percentile in the majority of tests performed on the full sample period, while generally showing higher t-statistics than in the 10th percentile. All in all, given the previously mentioned diversification problems in the 10th and 90th percentiles, it can be considered a strong indication that H1 holds for these samples as well.

Therefore, it is evident that the main hypothesis (H1) still holds following the robustness tests. Especially when taking into account the absolute values of $t(\overline{\hat{\gamma}}_{CMA} = \overline{CMA})$, which are generally lower in the higher percentiles, and definitely lowest in the 75th percentile.

However, regarding the relationship described in the secondary hypothesis (H2), it is more difficult to make conclusions after performing the robustness tests. The negative development of average asset use efficiency over time is correlated with the CMA factor being less significant in the short period data sample, but following the robustness tests, the findings are to be considered uncertain. Given the overall lower t-statistics in all samples during the sub-period, even in the 90th percentile where the asset use efficiency is still relatively high, it is impossible to say if the decrease in the overall significance of the CMA factor is truly due to the decrease in asset use efficiency. It is equally likely that the lower t-statistics are due to the fewer observations and the lower average CMA.

With these empirical conclusions as a foundation, the paper continues with a less empirically-driven discussion of the results after the limitations have been considered.

4.4 Limitations

There are some shortcomings associated with the empirical findings in this paper that should be addressed. The relevant areas to elaborate on are measurement error, autocorrelation, the choice of sample firms, sample selection bias, the choice of asset pricing model, the estimation of the investment variable, the sorting of portfolios and lastly, the trade-off between using portfolios and individual securities.

4.4.1 Measurement error

The Fama-MacBeth (1973) regression methodology suffers from a well-known errors-in-variables bias. Remembering the methodology whereby estimates of beta are first obtained from running separate time series regressions for each asset. Thereafter, the gammas are estimated from a cross-sectional regression using the estimated betas. Therefore, the explanatory variables used in the second stage cross-sectional regression are estimated with errors. This inherent difference between the true values and the measured values in the Fama-MacBeth regression methodology creates an error-in-variables problem that could distort results.

4.4.2 Autocorrelation

Another possible source of error, related to the regression methodology, is autocorrelation. The Fama-MacBeth (1973) regression methodology only provides standard errors that are corrected for cross-sectional correlation between the explanatory variables. Since autocorrelation is stronger over a long time horizon, and considering the length of the full time period of this study, the results obtained may be at risk of serial correlation.

4.4.3 The choice of sample firms

In this paper both active and inactive firms are included in the data set. Arguably, this clears the data from a potential survivorship bias. However, including inactive firms may cause another bias as these firms may exhibit strange fundamental data during their last active years, such as not generating any sales, which would lower their level of AT. As a result, the observations pertaining to inactive firms may reduce the explanatory power of the asset pricing tests.

Moreover, the data sample does not include financial services firms, which is in line with previous literature. Including these firms could have caused a bias as they generally show low AT. Thus, the 10th AT percentile studied in this paper would have been mostly constituted of financial services firms.

4.4.4 Sample selection bias

In the data collection process, fundamental data and monthly returns are matched as previously discussed in detail. A data availability bias could exist whereby larger firms might be over-represented, given that these firms are more likely to have data available.

4.4.5 The choice of asset pricing model

This paper only investigates the investment variable when included in the FF-5F model. Given the high correlation established between three of the variables included in the regression (the HML, RMW and CMA factors), the explanatory power of the investment variable may look different if, for instance, Carhart's (1997) four-factor model that includes a momentum factor was to be tested.

4.4.6 The proxy for the investment variable

Referring back to the equation for the rationale of the investment variable, also shown below, the variable should be defined as growth in the book value of equity. Fama and French (2015) acknowledges this definition in their paper and show that using growth in assets instead of equity yields roughly the same results, with the main difference being that sorting on asset growth produces slightly larger spreads in average returns. However, considering the presence of debt in the balance sheet, the growth in assets is not necessarily an appropriate proxy of the true variable, growth in equity, all the time.

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) / (1+r)^{\tau}}{B_t}$$

Additionally, the valuation equation puts forward evidence that B/M is a noisy proxy when estimating expected returns as well, since the ME also corresponds to forecasts of earnings and investments.

4.4.7 The sorting of portfolios

Although the variations of sorts have been thorough in this paper, the choice of sorts is inevitably affecting the final results. Fama and French (2015) find that average r-square is lower in portfolios that use three sorts compared to portfolios using two sorts. As conditional sorts are used in this paper, thereby remedying the issue of correlation between variables, the variations in average r^2 are mostly due to the difference in the amount of portfolios produced.

4.4.8 The trade-off between using portfolios and individual stocks

The reason for sorting into portfolios is that it, as previously mentioned, reduces the idiosyncratic volatility. However, portfolios also destroy information by shrinking the dispersion of betas, leading to larger standard errors. Performing the tests on individual stocks might change the outcome but will not be tried in this paper.

5. Discussion

This section will first discuss the empirical results further by comparing them to the findings of previous research on the subject. Thereafter, the wider implications of the findings of this paper will be presented, which moves the discussion section towards an attempt to further understand the empirical results. This includes investigating the average development for all firms, as well as relevant AT percentiles, both in terms of key metrics associated with the CMA factor and AT.

5.1 Results compared to existing literature

As depicted more thoroughly in the literature section, Aharoni et al. (2013) used the same two-stage regression methodology as in this study to find a negative relationship between investments and average returns. Moreover, their results are in line with the findings of Fama and French (2015), Titman et al. (2004), Fairfield et al. (2003) and Richardson et al. (2003) who also found statistical significance for the same relationship that firms investing aggressively show lower subsequent average returns. Although investigating the presence of this relationship is not the focus of this paper, the findings regarding the investment variable in the different AT percentiles are in accordance with previous literature that have studied the CMA factor in an asset pricing model context.[34]

The focus of this paper has rather been on studying the CMA factor by using the relevant AT percentiles to uncover differences in the behaviour of the factor between firms and over time. In this specific field, there is a lack of existing papers to compare the empirical results with. Therefore, the findings could potentially have wide implications and a discussion of the underlying drivers of the variable could add relevant insights to the results.

5.2 The wider implications

Given the empirical findings that the CMA factor is not significant for all time periods and AT percentiles studied, the feasibility of the one-fits-all theory can be questioned. Additionally, the results suggests that models tailored to certain subgroups, based on firm characteristics, are instead preferred in most

[34] See table (13) in Appendix I

practical cases. The FF-5F model has been shown in numerous studies to perform well when predicting returns for the overall market. However, in practice, that is seldom the aim. Oftentimes, the returns that one wishes to predict can be categorised to a subcategory of firms that might not be representative of the overall market, in such cases a more focused model could have more predictive power. A relevant example is the evaluation of fund manager performance, which is commonly done using either the CAPM or the FF-3F model, and arguably the FF-5F model going forward. Even though this paper does not study the CAPM or FF-3F model, for arguments sake it is expected that these behave similarly to the FF-5F model, which seems reasonable given that they are also general asset pricing models. Few fund managers invest in all industries, types of firms and markets, rendering the common asset pricing models to general to predict returns according to this study. Say for example that one manager invests in industries characterised by low asset use efficiency, using the FF-5F model to evaluate her returns in that case could predict alphas that are unreliable due to a misuse of the CMA factor.

Another important implication is for managers of public companies that are concerned with firm valuation. An imperfect understanding of the true exposures of the company might lead management to make imperfect decisions.[35] According to the results of this study, a manager of a firm with low asset use efficiency need not necessarily be concerned with the effect that her firm's level of investments might have on its expected return and firm value. All of this is of course given that the CMA factor accurately captures the expected risk premium for investing aggressively versus conservatively.

The process of making an asset pricing model more focused towards a subgroup involves studying the drivers of the independent variables that are used as inputs to the model. Therefore, the remainder of the discussion will be focused on understanding the empirical results for the CMA factor by investigating its underlying forces more thoroughly.

In terms of wider context, studying the remaining factors of the model entail understanding each factor in a similar manner, thereby figuring out when the asset pricing model is applicable. However, this process will not be undertaken in this paper.

[35] Fama and French (1997) report large standard errors in the estimation of the cost of equity on industry-level depending on which asset pricing model that is used

5.3 Analysis of the investment variable using DuPont

Naturally, the key metric to further investigate is the AT ratio which captures the asset use efficiency of firms and has been the focus of this paper. However, the ROA, which uses the AT as a component in the DuPont equation, will also be discussed.[36]

5.3.1 The discussion data sample

Before delving into the discussion, it should be mentioned that the data sample used in this section includes slightly more firms than the one used in the regressions. Firstly, fundamental data that could not be matched with returns was excluded from the regressions but is included in this section. Additionally, to be included in the regressions 24 months of consecutive fundamental data was needed, which is not a basis for exclusion in this section.

The figures used in the discussion include all firms in the data sample. Yet in some instances, alternative graphs are included that exclude outliers at the 1% and 99% level for illustrative purposes. Graphs excluding outliers are interesting to lightly study since the narrower spans between min and max values make them easier to interpret. However, one should be careful studying these in connection to this papers empirical results as they effectively have removed 10% of the observations in the outer percentiles studied, and 4% of the remaining percentiles.

5.3.2 The asset turnover ratio

A pivotal part of the process to further understand the empirical results is to study the AT ratio used to split the data set into percentiles. As described previously, AT can be considered a measurement of the asset use efficiency of firms, which for instance incorporates how efficient the firms are in their use of PPE as well as the efficiency of their working capital management. Figure (2) in Appendix IV shows the development of AT over time for all firms included in the discussion data. Similarly to the findings in existing literature on the AT metric[37], one can first conclude that the development over time for the AT in this data sample is more resistant than profit

[36] The full set of graphs is available in Appendix IV
[37] Fairfield and Yohn (2001), Nissim and Penman 2001, Penman and Zhang (2003)

margin.[38] Although firms can employ different tactics to maintain a healthy profit margin[39], oftentimes economies of scale serve as a natural protection of AT ratios from competition.[40]

Moreover, in the empirical results it was also concluded that a negative slope over time of AT is observed, which is a puzzling finding. The logical reasoning behind expecting a positive slope would be that assets are becoming increasingly efficient and thus, firms should be able to generate more sales for each asset unit. However, the observed slope is actually not contradictory to this notion. Although it might be true that the asset base is experiencing increased efficiency for many industries, it leads firms to arguably expand their asset base as these assets are smaller, cheaper and better. The economic reason for a negative trend could perhaps pertain to a diminishing marginal revenue on assets on an industry level, whereby cheaper assets also results in cheaper products and services. This theory is supported by the fact that figure (10) shows that average net sales for all firms has steadily increased over the full time period, meaning that the negative slope pertains to a relatively higher level of asset accumulation in dollar terms. However, it is difficult to discuss the development further as total assets incorporates such a wide variety of assets, each with different characteristics.

Although the average of all firms provides some interesting insights, in order to truly understand the development of the AT on a firm level, one should consider studying more subcategories, such as industry averages, as some industries will inherently display a higher AT ratio. However, the sub-samples based on AT percentiles presented in figure (3) in Appendix IV give an indication that the negative development is a market-wide phenomenon, and the fundamentals described above give no reason to expect a halt in the development. Given the statistical relationship found between the AT variable and the CMA factor in the empirical results, the overall development towards lower asset use efficiency indicates that the CMA factor will become less significant over time. If the trend continues, learning to apply the FF-5F model might be equivalent to reading the owner's manual of a sinking ship. To prove this hypothesis, further tests with more time periods are needed, which provides an interesting opportunity for future research.

[38] Comparing graph (2) and graph (4)
[39] Including brand name recognition, customer loyalty, favourable contracts with market players and legal barriers such as patents
[40] Soliman (2008) argues that this involves the costly process of making production more efficient

5.3.3 ROA

It is also interesting to briefly investigate the development of ROA over time as it is a metric closely related to AT through the previously described DuPont equation, which explains how asset use efficiency is related to the returns of a firm.

The figure (7) presents the development of average ROA over time, which is a measure of the returns that a company earns on its total assets, indicating how efficient a firm is at generating profits from its assets. The metric shares the decreasing slope of the average AT but it is much more severe as it incorporates the less resistant average profit margin. The slope of the average ROA is explained by Romer (1986) who argue that knowledge is easily transferred throughout an economy, making returns transitory and diminishing. This is a potential explanation for the decreasing marginal revenues on assets discussed in the AT section as well.[41] Besides the notion that products and services are becoming relatively more cheap, another possible force of diminishing ROA comes from the general business environment and the increased competition from globalisation.

The graph (9) indicates that firms in each relevant AT percentile are finding it increasingly hard to generate returns from their asset bases, but the lower AT percentiles have experienced a significantly larger deterioration of ROA over time. Thus, contrary to popular belief, it would not seem that firms with a low AT compensate for this with high profit margins.[42] The profit margins based on the AT percentiles presented in Appendix IV further provide evidence against the common perception that firms with low AT tend to have high profit margins as part of a pricing strategy, if outliers are excluded. The fact that firms with a higher level of AT earn a higher ROA is consistent with a BCG report[43] on the subject, although their analysis compared firms within the same industry.

Using the DuPont analysis, this study arrives at two important insights for the findings of this paper. Firstly, AT is inherently more resilient than ROA and thus more appropriate for predictions. Secondly, marginal revenue on assets seems to be decreasing, which explains the decrease of the AT ratio and, given the previously discussed forces, the trend is expected to continue.

[41] If large scale production (in the whole economy) leads to increased knowledge transfer, resulting in increased competition for quantities and lower prices.
[42] If one considers all firms however, the 10th percentile is in fact displaying the largest profit margins in the later part of the time period thereby making the relationship weaker
[43] When "Asset-Light" is Right (2014)

6. Conclusion and further research topics

6.1 Key takeaways

The purpose of this study has been to investigate the behaviour of the CMA factor in the FF-5F model. Apart from finding indications in line with previous research, stating that firms investing aggressively are subject to lower subsequent returns, the model illustrated satisfactory predictive power when tested using a two-stage Fama-MacBeth regression methodology. Most importantly though, two hypotheses were tested.

The main hypothesis stated that the CMA factor was expected to be more significant when predicting returns for asset use efficient companies than inefficient ones. The hypothesis proved to be robust since it was resilient for all variations of portfolio sorts, periods and return definitions used in the tests.[44] A systematic pattern of higher statistical significance was displayed for the CMA factor when the FF-5F model was estimated using a sample containing firms in the 75th percentile of AT than when it was estimated using a sample of firms in the 25th percentile. Though not as striking, a similar pattern could also be observed when comparing the 90th percentile to the 10th percentile.

The secondary hypothesis was twofold in that it expected the average asset use efficiency to increase over time and, because of that, the significance of the CMA factor to increase as well. First of all, this hypothesis had to be rejected straight away due to an interesting finding that asset use efficiency have, in fact, been decreasing over time. Secondly, it proved difficult to conclude that the observed significance levels of the CMA factor follow the development of asset use efficiency over time, although it could not be rejected either. However, the trend of AT, as well as a discussion[45] of its underlying drivers, still serve as a basis to question whether the variable will be relevant when predicting variances in returns going forward.

An additional, and accidental, finding of this paper is that by sorting the data into at percentiles and sorting the assets into portfolios using a 2x3x3 sort on *Size*, *Value* and *Inv*, one effectively captures differences in both portfolio returns and portfolio exposures to the profitability factor (RMW) of the FF-5F model. This could be important since Fama and French (2015) cannot explain the relationship between negative exposures to RMW and low

[44] See Appendix II
[45] See Discussion section

profitability for the portfolios in which they have problems predicting returns. The finding is an indication that AT should be tested as a potential variable for factor construction.

6.2 Remaining, unanswered questions

As presented in the empirical results, even though the CMA factor is found to be insignificant for asset use inefficient companies, it does not necessarily mean that the factor should be dropped from the FF-5F model all together. For instance, it still correlates with other factors of the model, and dropping it could potentially bias betas for other factors or significantly decrease the explanatory power of the model. In order to truly understand how to best, if at all, amend the FF-5F for application on asset use inefficient firms, further research must be conducted on the effect of dropping the CMA factor from the model. The empirical research involved in the estimation of a new asset-pricing model is however far outside the scope of this paper. Such research would require reconstructing the factors in the FF-5F since they currently control for each other, and controlling for an omitted characteristic could distort the results.

Related to the previous unanswered question is a second one, which should be researched further. It is possible that the results obtained in this study are due to the factor constructions tested. If other versions of the FF-5F factors were to be tested, especially for the CMA factor, other results might be displayed in the same tests.

6.3 Directions for future research

Several suggestions for future directions of research that could potentially add further understanding to the CMA factor and the FF-5F model have appeared during the course of this study. In addition to these, there are a few interesting subjects related to the study where the authors of this paper would expect one to find relevant results.

First of all, it would be intriguing to study the CMA factor using another asset pricing model, to determine whether it behaves in a similar manner in other model specifications. If it does, this proof would further cement the robustness of the main hypothesis. Furthermore, it would ensure that the relationship between the CMA factor and AT found in this paper is truly due to the reasoning behind the main hypothesis and not due to an unfortunate anomaly or interaction effect between the variables of the FF-5F.

Testing whether the CMA factor behaves differently in certain macroeconomic environments could be important as well. For instance, it could be argued that firms that invest aggressively during a recession should earn higher subsequent returns since they are buying relatively cheap assets. If this were the case, the CMA factor would display opposite signs during recessions, which in turn would lower the average premium awarded to firms for an exposure to the factor during recessions. All things equal, this would make it harder to find statistically significant average premiums for the factor during periods partly including recessions. Such a finding could have important implications for the interpretation of this paper, since the period after 1990 that was tested includes the severe financial crisis of 2007-2008; thus, it might not be comparable to the full sample period tested.

Finally, but arguably most interesting, this paper suggests that research is conducted on the applicability of AT as a variable for creating an asset use efficiency factor. Results have been found to support a hypothesis that the AT is positively correlated with both average excess returns and average exposure to the profitability (RMW) factor, which suggests that the variable can be used to create a factor exchangeable with the RMW factor. What is most intriguing with this finding is that Fama and French (2015) cannot fundamentally explain the negative exposures observed to the RMW factor for portfolios in which the FF-5F model is unable to accurately predict returns.

References

Periodicals

Aharoni, G., Grundy, B., Zeng, Q., 2013, Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis, Journal of Financial Economics 110, 347-357.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, Journal of Financial Markets 5, 31-56.

Ang, A., Hodrick, R., Xing, Y., and Zhang, X., 2009, High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence, Journal of Financial Economics 91, 1-23.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, Journal of Financial Economics 9, 3-18.

Black, Fischer, 1972, Capital Market Equilibrium with Restricted Borrowing, Journal of Business, 444-455.

Carhart, M., 1997, On persistence in mutual fund performance, Journal of Finance 52, 57-82.

Chan, Louis K., Yasushi Hamao, and Josef Lakonishok, 1991, Fundamentals and stock returns in Japan, Journal of Finance 46, 1739-1789.

Douglas, G. W., 1969, Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency, Yale Econ. Essays 9, 3-45.

Fairfield, P., and T. Yohn, 2001, Using asset turnover and profit margin to forecast changes in profitability, Review of Accounting Studies (December), 371–385.

Fairfield, P., Whisenant, S., Yohn, T., 2003, Accrued earnings and growth: Implications for future profitability and market mispricing, The Accounting Review 78, 353–371.

Fama, Eugene F. and Kenneth R. French, 1992, The cross-section of expected stock returns, Journal of Finance 47, 427-465.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3–56.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. Journal of Financial Economics, 43(2), 153-193.

Fama, Eugene F. and Kenneth R. French, 2006, Profitability, investment, and average returns, Journal of Financial Economics 82, 491–518.

Fama, Eugene F. and Kenneth R. French, 2008, Dissecting anomalies, Journal of Finance 63, 1653-1678.

Fama, Eugene F. and Kenneth R. French, 2015, A five-factor asset pricing model, Journal of Financial Economics 116, 1-22.

Fama Eugene F. and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 81, 607-636.

Friend, Irwin and Marshall Blume, 1970, Measurement of Portfolio Performance under Uncertainty, The American Economic Review 60, 561-75.

Gibbons, Michael R., Steven A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, Econometrica 57, 1121–1152.

Graham, John R., and Harvey R. Campbell, 2001, The theory and practise of corporate finance: evidence from the field, Journal of Financial Economics 60, 187-243.

Ikenberry, D., Lakonishok, J., Vermaelan, T., 1995, Market underreaction to open market share repurchases, Journal of Financial Economics 39, 181–208.

Jegadeesh, N., and Titman, S., 1993, Returns to Buying winners and Selling Losers: Implications for Stock Market Efficiency, Journal of Finance 48, 93-130.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics 47, 13–37.

Loughran, T., Ritter, J., 1995, The new issues puzzle. Journal of Finance 50, 23–51.

Markowitz, Harry, 1952, Portfolio Selection, Journal of Finance 7, 77-91

Miller, M. and Modigliani, F., 1961, Dividend policy, growth, and the valuation of shares, Journal of Business 34, 411-433.

Nissim, D., and S. Penman, 2001, Ratio analysis and equity valuation: From research to practice, Review of Accounting Studies (March), 109–154.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium, Journal of Financial Economics 108, 1-28.

Pástor, L., Stambaugh, R., 2003, Liquidity risk and expected stock returns, Journal of Political Economy 111, 642-685.

Romer, P., 1986, Increasing returns and long-run growth, Journal of Political Economy 94, 1002–1037.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, Journal of Portfolio Management 11, 9-17.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance 19, 425–442.

Sloan, R.G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting Review 71, 289–315.

Soliman, Mark T., 2008, The Use of DuPont Analysis by Market Participants, The Accounting Review 83, 823-853

Stattman, Dennis, 1980, Book values and stock returns, The Chicago MBA: A Journal of Selected Papers 4, 25-45.

Titman, S., Wei, K., Xie, F., 2004, Capital investments and stock returns, Journal of Financial and Quantitative Analysis 39, 677-700.

Tobin, James, 1958, Liquidity Preference as Behavior Towards Risk, The Review of Economic Studies XXV, 65-86.

Unpublished papers

Agarwal, V., Bakshi, G., Huij, J., 2008, Higher-moment equity risk and the cross-section of hedge fund returns, Working Paper, Robert H. Smith School of Business, University of Maryland, US.

Black, Fischer. Michael C. Jensen., and Myron Scholes., 1972, The capital asset pricing model: Some empirical tests, M. Jensen. ed. Studies In the theory of capital markets , Praeger, New York, NY.

Fama, Eugene F. and Kenneth R. French, 2015, International Tests of a Five-Factor Asset Pricing Model, Working paper, Tuck School of Business.

Hou, K., Xue, C., Zhang, L., 2012. Digesting anomalies: An investment approach. Unpublished working paper. The Ohio State University

Hou, K., Xue, C., and Zhang, L., 2015, A Comparison of New Factor Models, Fisher College of Business Working Paper, Columbus, Ohio State University.

Markowitz, Harry, 1959, Portfolio Selection: Efficient Diversification of Investments, Wiley, New York, NY.

Moerman, G. A. (2005). How Domestic is the Fama and French Three-Factor Model? An Application to the Euro Area.

Penman, S., and X. Zhang, 2003, Modeling sustainable earnings and P/E ratios using financial statement information, Working paper, Columbia University.

Richardson, S.A. and Sloan, R.G., 2003, External financing and future stock returns, Unpublished working paper, University of Pennsylvania, Philadelphia, PA.

Data sources

French, Kenneth R., Online database, Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data˙library.html, Accessed: September 21, 2016.

Wharton Research Data Services (WRDS), Online database for COMPUSTAT and CRSP, Available at: https://wrds-web.wharton.upenn.edu/wrds/, Accessed: September 24, 2016

Articles in the popular press

The Boston Consulting Group (BCG), When "Asset Light" Is Right, September 2014, Available at: https://www.bcgperspectives.com/content/articles/business˙unit˙strategy˙value˙creation˙growth˙when˙asset˙light˙is˙right/?chapter=2

Appendices

I. Data description

Average monthly excess returns for the 2x3x3 sort and for the relevant asset turnover (AT) percentiles. It shows returns for the full time period (January 1968 to December 2015) and returns including dividends.

Table 13: Average excess returns for portfolio formed on Size. B/M and Inv

Size		Small			Big		
Panel A: 10^{th} percentile							
B/M	Low	2	High	Low	2	High	Average
Low inv	0.01819	0.01126	0.01955	0.0072	0.00669	0.00728	
2	0.00859	0.01163	0.01384	0.00107	0.00363	0.00548	
High inv	0.00657	0.00825	0.01106	-0.00018	0.00315	0.00547	
$\boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-0.01162	-0.00301	-0.00849	-0.00738	-0.00354	-0.00181	-0.00598
$\%\ \boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-63.9%	-26.7%	-43.4%	-102.5%	-52.9%	-24.9%	-52.4%
$\boldsymbol{t}(\overline{\boldsymbol{Low}} = \overline{\boldsymbol{High}})$	2.01310	0.69039	1.77888	2.25906	1.22370	0.77113	1.45604
Panel B: 25^{th} percentile							
B/M	Low	2	High	Low	2	High	Average
Low inv	0.01239	0.01497	0.01912	0.00762	0.00703	0.00789	
2	0.00833	0.00952	0.0133	0.00463	0.00673	0.00889	
High inv	0.00373	0.01259	0.01091	0.00388	0.00632	0.00701	
$\boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-0.00866	-0.00238	-0.00821	-0.00374	-0.00071	-0.00088	-0.00410
$\%\ \boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-69.9%	-15.9%	-42.9%	-49.1%	-10.1%	-11.2%	-33.2%
$\boldsymbol{t}(\overline{\boldsymbol{Low}} = \overline{\boldsymbol{High}})$	2.53756	0.82061	2.99150	1.80375	0.36656	0.55241	1.51206
Panel C: 75^{th} percentile							
B/M	Low	2	High	Low	2	High	Average
Low inv	0.01718	0.01679	0.02081	0.00764	0.01149	0.01331	
2	0.00874	0.01352	0.01887	0.00559	0.01194	0.01026	
High inv	0.00773	0.01009	0.01371	0.00728	0.01066	0.00983	
$\boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-0.00945	-0.0067	-0.0071	-0.00036	-0.00083	-0.00348	-0.00465
$\%\ \boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-55,0%	-39.9%	-34.1%	-4.7%	-7.2%	-26.1%	-27.8%
$\boldsymbol{t}(\overline{\boldsymbol{Low}} = \overline{\boldsymbol{High}})$	3.31282	2.90466	2.91889	0.20498	0.54624	2.11240	2.00000
Panel D: 90^{th} percentile							
B/M	Low	2	High	Low	2	High	Average
Low inv	0.01537	0.02184	0.01657	0.00908	0.01162	0.01024	
2	0.01668	0.01362	0.02532	0.00469	0.01222	0.00994	
High inv	0.00712	0.00942	0.01293	0.00833	0.01175	0.01304	
$\boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-0.00825	-0.01242	-0.00364	-0.00075	0.00013	0.0028	-0.00369
$\%\ \boldsymbol{Diff}\ (\overline{\boldsymbol{High}} - \overline{\boldsymbol{Low}})$	-53.7%	-56.9%	-22,0%	-8.3%	1.1%	27.3%	-18.8%
$\boldsymbol{t}(\overline{\boldsymbol{Low}} = \overline{\boldsymbol{High}})$	1.70839	3.1644	1.06204	0.28100	-0.05173	-1.14806	0.83601

Table 14: Summary statistics for factor returns

	1968			1990		
Factor (f)	$\bar{R}_f$	$s(R_f)$	$t(\bar{R}_f)$	$\bar{R}_f$	$s(R_f)$	$t(\bar{R}_f)$
MktRF	0.00489	0.04554	2.59439	0.00615	0.04313	2.54913
SMB	0.00189	0.03058	1.49645	0.00182	0.03084	1.05420
HML	0.00364	0.02881	3.05007	0.00211	0.02995	1.26083
RMW	0.00260	0.02304	2.72672	0.00342	0.02756	2.21821
CMA	0.00353	0.02021	4.22201	0.00249	0.02096	2.12169

The MktRF factor is the equally-weighted monthly return of all firms in the data sample less the US 1-month Treasury bill rate. SMB is defined as the equal weighted average of the portfolio returns of small firms minus the equal weighted average portfolio returns of big firms. HML, is defined the equal weighted average portfolio returns of the two high *B/M* portfolios minus the equal weighted average portfolio returns of the two low *B/M* portfolios. RMW is the equal weighted average portfolio returns of the two robust *OP* portfolios minus the equal weighted average portfolio returns of the two weak *OP* portfolios. CMA is the equal weighted average portfolio returns of the two conservative portfolios minus the equal weighted average portfolio returns of the two aggressive portfolios. All stocks are assigned to groups at the end of June fiscal year t.

II. Summary tables of regressions

The summary tables presented below depicts the regressions results in four different variations, all including the AT percentiles studied in this paper and the portfolio sorts for each of these percentiles. The four variations are displayed in the following order: 1. Full time period and returns including dividends, 2. Later time period and returns including dividends, 3. Full time period and returns excluding dividends and, 4. Later time period and returns excluding dividends.

Again, the full time period considered is January 1968 to December 2015 whilst the later period is defined as January 1990 to December 2015.

In turn, the tables present statistics for each variation of the regression results in the following order: the gamma value of CMA, the standard error of this estimate, t-statistics to test whether the gamma is statistically different from zero, t-statistics to test if the gamma of CMA is equal to the CMA factor, the gamma of the alpha with corresponding t-statistics to see whether it is statistically different from zero and lastly, the r-square of the model and the corresponding standard error.

Regression results for full period using returns including dividends

		$\overline{\hat{\gamma}}_{CMA}$	$s(\hat{\gamma}_{CMA})$	$t(\overline{\hat{\gamma}}_{CMA}=0)$	$t(\overline{\hat{\gamma}}_{CMA}=CMA)$	$\overline{\hat{\gamma}}_0$	$t(\overline{\hat{\gamma}}_0=0)$	$\overline{r^2}$	$s(r^2)$
10th	5x5	-.00099383	.03170335	-.74447171	-3.0339582	.01527285	4.717086	.32391994	.15868166
	5x5	.00076959	.03041584	.59447194	-1.9895954	.01364439	4.1647336	.33035467	.16363083
	2x3x3	.00125007	.03480108	.8439409	-1.4409117	.01123291	3.0111036	.42260493	.18111505
	2x4x4	.0009748	.02644509	.8660466	-2.0136384	.01348484	4.6194775	.28080158	.14582014
	2x2x2x2	.00160941	.04094089	.92359219	-1.0561419	.00950169	2.4483425	.46163901	.19701532
25th	5x5	.00186054	.02932698	1.5066472	-1.1288923	.01231665	4.6308799	.38800822	.18305591
	5x5	.00189925	.03091665	1.44331	-1.142736	.01165543	4.005726	.37398521	.1770536
	2x3x3	.00230285	.03373925	1.6036151	-.84362406	.00819754	2.689526	.46820298	.19707617
	2x4x4	.00299023	.02719985	2.5829001	-.4293803	.00733107	2.9365274	.3146775	.16571294
	2x2x2x2	.00303993	.03673605	1.9442012	-.31585787	.00691327	2.1950684	.51350047	.19204816
75th	5x5	.00297796	.02830396	2.4986871	-.29765464	.01760757	5.7643785	.3330491	.16471374
	5x5	.00422678	.02870459	3.4596137	.53524534	.01206556	4.3174338	.32263389	.1601906
	2x3x3	.00348346	.03248628	2.5193052	-.03134496	.00650251	2.1466622	.40264487	.17926889
	2x4x4	.00245708	.02615564	2.207108	-.9021759	.01199672	4.8342632	.24740261	.1315232
	2x2x2x2	.00417091	.03452778	2.838127	.42674623	.01812741	5.0820808	.44245774	.18454336
90th	5x5	-.00101974	.02972798	-.81463265	-3.3784341	.00801228	2.7336838	.28885533	.14931372
	5x5	.0011746	.02995393	.92130824	-1.7296435	.01166476	4.1317041	.2736265	.14500197
	2x3x3	.00277218	.03266756	1.9937697	-.51384777	.01083702	2.8392387	.37078731	.16584409
	2x4x4	.00191228	.02652228	1.6939903	-1.3103137	.01110008	4.1617732	.22774064	.12282455
	2x2x2x2	.0039638	.03486796	2.6708808	.27980127	.01298364	3.4350627	.39142472	.18283254

			$\overline{\hat{\gamma}}_{CMA}$	$s(\hat{\gamma}_{CMA})$	$t(\overline{\hat{\gamma}}_{CMA}=0)$	$t(\overline{\hat{\gamma}}_{CMA}=CMA)$	$\overline{\hat{\gamma}}_0$	$t(\overline{\hat{\gamma}}_0=0)$	$\overline{r^2}$	$s(r^2)$
Regression results for late period using returns including dividends	10th	5x5	.00050203	.03284821	.26995503	-.93127051	.01565263	3.4545209	.30370234	.14931679
		5x5	.0014375	.03073432	.82615366	-.51006744	.01249248	2.8809438	.29629252	.15374488
		2x3x3	.00192651	.03476193	.97891569	-.22243656	.01273965	2.3439552	.41580513	.18137884
		2x4x4	.00169573	.02649518	1.1304891	-.41096554	.01329576	3.2963539	.25882654	.13481177
		2x2x2x2	.00316401	.03876011	1.4418845	.33889521	.00548426	1.0179277	.44282166	.19199695
	25th	5x5	-.00134873	.0282679	-.84277151	-2.1023227	.01754557	4.6489179	.39525452	.18979909
		5x5	.00090929	.03079727	.52151355	-.76307847	.0131528	3.2584912	.40040736	.18427769
		2x3x3	.00040415	.03112424	.22936162	-1.0884456	.00954164	2.376356	.49821559	.20101092
		2x4x4	.00259269	.02613988	1.7519571	.11596066	.0074303	2.2345756	.33112718	.17421383
		2x2x2x2	.0003715	.03337928	.19658722	-1.1056979	.00934764	2.3896303	.52545877	.20110685
	75th	5x5	.00182088	.02804468	1.1468548	-.33256843	.01501361	3.518581	.35483197	.16481564
		5x5	.00278303	.02802514	1.7540722	.22718649	.01186089	3.1909576	.34382259	.16871419
		2x3x3	.00274788	.03267465	1.4854692	.19121129	.00534787	1.3335281	.41376387	.18200118
		2x4x4	.00277221	.02597318	1.8852921	.23998721	.01073067	3.1237529	.26163765	.13589814
		2x2x2x2	.00228844	.03191874	1.2663987	-.06036994	.01032833	2.3794454	.45848541	.19267312
	90th	5x5	-.00165827	.03008884	-.97348082	-2.2949024	.00615807	1.5365454	.28583402	.14711111
		5x5	.00074052	.02922717	.44753781	-.93553311	.01432379	3.6170764	.28507195	.14780272
		2x3x3	.0034208	.03235541	1.8674893	.50764231	.01276176	2.3615351	.37581357	.16653522
		2x4x4	.00215669	.02676015	1.4235624	-.14274891	.01201258	3.233415	.23534766	.12416589
		2x2x2x2	.00259251	.03296549	1.3891147	.09000924	.00817585	1.6318834	.39073392	.18363962

Regression results for full period using returns excluding dividends

Percentile	Portfolio	$\overline{\hat{\gamma}}_{CMA}$	$s(\hat{\gamma}_{CMA})$	$t(\overline{\hat{\gamma}}_{CMA}=0)$	$t(\overline{\hat{\gamma}}_{CMA}=CMA)$	$\overline{\hat{\gamma}}_0$	$t(\overline{\hat{\gamma}}_0=0)$	$\overline{r^2}$	$s(r^2)$
10th	5x5	-.00123716	.0316254	-.92903219	-3.208313	.01159014	3.5802513	.32228174	.1579643
10th	5x5	.00062116	.03064389	.47624528	-2.0824346	.00936619	2.850775	.32911654	.16248269
10th	2x3x3	.00090204	.03486701	.60782698	-1.6592626	.00678419	1.8173999	.42123711	.18127086
10th	2x4x4	.00072317	.02633261	.64523123	-2.2182801	.00906995	3.1083352	.27908217	.14394722
10th	2x2x2x2	.00158479	.04177074	.8913904	-1.0509158	.00483049	1.2386647	.45992893	.19573407
25th	5x5	.00140035	.02931978	1.1342672	-1.4710516	.00835974	3.1363144	.38647222	.18210719
25th	5x5	.00158637	.03085983	1.2077571	-1.3644153	.00759713	2.6059651	.37378682	.17720421
25th	2x3x3	.00158967	.03373501	1.1071247	-1.3317951	.0034867	1.1426102	.46745026	.19669353
25th	2x4x4	.00234187	.0270035	2.0375686	-.9492297	.00283169	1.1401224	.31331046	.16462502
25th	2x2x2x2	.00229106	.03644935	1.476779	-.806083	.0022504	.71615744	.51208167	.19185751
75th	5x5	.00276354	.02825884	2.3224731	-.46208768	.01574055	5.2135017	.33205231	.16467844
75th	5x5	.00406247	.02863721	3.3329509	.41015107	.00986404	3.5384031	.32257881	.16040722
75th	2x3x3	.0032204	.03264476	2.3177477	-.22036395	.00448349	1.4880876	.40145972	.17851612
75th	2x4x4	.00224911	.02631043	2.0084075	-1.0720688	.00961201	3.8774174	.24718642	.13121292
75th	2x2x2x2	.00403157	.03437826	2.755241	.33586589	.01601797	4.494814	.44141228	.18508278
90th	5x5	-.00123955	.02971341	-.99072323	-3.5382051	.00581152	1.9900859	.28817678	.14917118
90th	5x5	.0011027	.0301433	.85948022	-1.7712707	.00959805	3.3887843	.27295431	.14448111
90th	2x3x3	.00248742	.03265369	1.7897218	-.70825972	.00855333	2.2447303	.36980507	.16559365
90th	2x4x4	.0017257	.026554	1.5268794	-1.4604974	.00876312	3.2943743	.22774319	.12309213
90th	2x2x2x2	.00375474	.03504134	2.5174949	.14548582	.01064575	2.8252515	.3912683	.18195374

Regression results for late period using returns excluding dividends

Percentile	Portfolio	$\overline{\hat{\gamma}}_{CMA}$	$s(\hat{\gamma}_{CMA})$	$t(\overline{\hat{\gamma}}_{CMA}=0)$	$t(\overline{\hat{\gamma}}_{CMA}=CMA)$	$\overline{\hat{\gamma}}_0$	$t(\overline{\hat{\gamma}}_0=0)$	$\overline{r^2}$	$s(r^2)$
10th	5x5	.00036773	.03285007	.19772773	-.99816238	.01328678	2.9300592	.30252831	.14950121
10th	5x5	.00136385	.03082868	.78142935	-.54775258	.00986521	2.2620929	.29535237	.15315796
10th	2x3x3	.00173257	.03450701	.88687376	-.31582438	.00928086	1.7060394	.41506273	.18177223
10th	2x4x4	.00160276	.02651342	1.0677752	-.46613477	.01027748	2.5427548	.25848001	.13363706
10th	2x2x2x2	.00316416	.03884445	1.4388194	.33878262	.00209284	.38628293	.4419808	.19170302
25th	5x5	-.00160927	.02809809	-1.0116468	-2.2545813	.01490912	3.9581589	.39397132	.18880891
25th	5x5	.00082386	.03082886	.47203139	-.80710529	.01000984	2.4641847	.40007311	.18499135
25th	2x3x3	.00005845	.03116389	.03312848	-1.2707514	.00619494	1.5427487	.49859184	.20032263
25th	2x4x4	.00230338	.02612035	1.5576315	-.05890025	.00429031	1.2918972	.33057781	.17305354
25th	2x2x2x2	-.00041215	.03321644	-.21917166	-1.5384919	.00611698	1.5588156	.52529868	.20164018
75th	5x5	.00166134	.02810981	1.0439451	-.42271724	.01377706	3.281712	.35364593	.16446841
75th	5x5	.00264136	.02792936	1.670488	.14290623	.01007604	2.7164086	.34341063	.16902869
75th	2x3x3	.00257138	.03291717	1.3798154	.09321656	.00405184	1.0171174	.41399889	.18106939
75th	2x4x4	.00260892	.02611929	1.7643157	.13393087	.00906253	2.6391872	.26232988	.13550326
75th	2x2x2x2	.00222641	.03183047	1.2354927	-.09394389	.00888048	2.0536815	.45902326	.19246545
90th	5x5	-.00177164	.03009412	-1.0398488	-2.3449212	.00467817	1.1672783	.28536293	.14664251
90th	5x5	.0006435	.02938941	.38675171	-.98497138	.0127867	3.2377944	.28503701	.14705046
90th	2x3x3	.00305447	.03225852	1.6725115	.32637477	.01106588	2.0504287	.3749452	.16568836
90th	2x4x4	.00203619	.02666469	1.3488341	-.21393864	.01025742	2.7734777	.23536919	.12395153
90th	2x2x2x2	.00236622	.03284659	1.2724544	-.01636674	.00641555	1.286852	.39081506	.18285526

III. Detailed regression results for the main sort of analysis

$$R_{p,t} - R_{f,t} = \hat{\gamma}_{0,t} + \hat{\gamma}_{MktRF,t} * \hat{\beta}_{MktRF,t-1} + \hat{\gamma}_{SMB,t} * \hat{\beta}_{SMB,t-1} + \hat{\gamma}_{HML,t} * \hat{\beta}_{HML,t-1} + \hat{\gamma}_{RMW,t} * \hat{\beta}_{RMW,t-1} + \hat{\gamma}_{CMA,t} * \hat{\beta}_{CMA,t-1} + \hat{\eta}_{p,t}$$

2x3x3 sort on Size, B/M and Inv, returns incl. dividends

Period	1968-2015				1990-2015			
Percentile	10th	25th	75th	90th	10th	25th	75th	90th
$\bar{\hat{\gamma}}_{MktRF}$	-.00463434	-.00283241	-.00022646	-.00314762	-.0058912	-.00405198	.00103871	-.00238842
$s(\hat{\gamma}_{MktRF})$	.08247399	.07069775	.07220792	.0774605	.08801121	.07536845	.07590002	.08604725
$t(\bar{\hat{\gamma}}_{MktRF})$	-1.3202008	-.94128213	-.07368441	-.95470995	-1.1823412	-.94963233	.24172851	-.49028687
$p(\bar{\hat{\gamma}}_{MktRF})$	.18731614	.34697278	.94128824	.34014305	.23797352	.34303647	.80914985	.62427663
$\bar{\hat{\gamma}}_{SMB}$	.00251439	.00559415	.00488521	.00519127	.0032115	.00740549	.00627321	.00605691
$s(\bar{\hat{\gamma}}_{SMB})$	.04662296	.04468119	.05305198	.05346779	.05040759	.05007421	.05917299	.06148018
$t(\bar{\hat{\gamma}}_{SMB})$	1.2670765	2.9415664	2.1634715	2.2811329	1.1253545	2.6122623	1.8725946	1.7401761
$p(\bar{\hat{\gamma}}_{SMB})$	.20566321	.00340287	.0309341	.02292135	.26130654	.00943115	.0620625	.08281727
$\bar{\hat{\gamma}}_{HML}$	.00251508	.00520572	.00600984	.00312333	.00354578	.00511447	.00539361	.00372257
$s(\bar{\hat{\gamma}}_{HML})$	.05051571	.04608039	.04556438	.04675199	.04920553	.04936748	.04722397	.04821853
$t(\bar{\hat{\gamma}}_{HML})$	1.1697545	2.654204	3.0988971	1.569592	1.2728424	1.8299411	2.0174113	1.3636591
$p(\bar{\hat{\gamma}}_{HML})$	.24260551	.00817925	.00204153	.11708413	.20402466	.06821581	.04451134	.17366109
$\bar{\hat{\gamma}}_{RMW}$	-.00041621	-.00256944	-.00131214	-.00106649	-.00012513	-.00272032	-.00266447	-.00324458
$s(\bar{\hat{\gamma}}_{RMW})$	.03395642	.03504483	.03496517	.03894334	.03425482	.03740681	.03479598	.0432875
$t(\bar{\hat{\gamma}}_{RMW})$	-.28798025	-1.7225997	-.8816848	-.64341697	-.0645216	-1.2845349	-1.3525657	-1.3239563
$p(\bar{\hat{\gamma}}_{RMW})$	.77347015	.08552205	.37833173	.52022127	.94859636	.19991085	.17717701	.18648984
$\bar{\hat{\gamma}}_{CMA}$	.00125007	.00230285	.00348346	.00277218	.00192651	.00040415	.00274788	.0034208
$s(\bar{\hat{\gamma}}_{CMA})$	.03480108	.03373925	.03248628	.03266756	.03476193	.03112424	.03267465	.03235541
$t(\bar{\hat{\gamma}}_{CMA})$	.8439409	1.6036151	2.5193052	1.9937697	.97891569	.22936162	1.4854692	1.8674893
$p(\bar{\hat{\gamma}}_{CMA})$	.39906868	.10937195	.01204044	.0466697	.3283825	.81873863	.13843252	.06277378
$\bar{\hat{\gamma}}_{0}$	.01123291	.00819754	.00650251	.01083702	.01273965	.00954164	.00534787	.01276176
$s(\bar{\hat{\gamma}}_{0})$	.08764682	.07161061	.07116836	.0896763	.09600315	.07092325	.07083638	.09545383
$t(\bar{\hat{\gamma}}_{0})$	3.0111036	2.689526	2.1466622	2.8392387	2.3439552	2.376356	1.3335281	2.3615351
$p(\bar{\hat{\gamma}}_{0})$	.00272233	.0073722	.03225605	.00468905	.01970971	.01808977	.18333441	.01881564

2x3x3 sort on Size, B/M and Inv, returns excl. dividends

Period	1968-2015				1990-2015			
Percentile	10th	25th	75th	90th	10th	25th	75th	90th
$\bar{\hat{\gamma}}_{MktRF}$	-.00346141	-.0009505	-.00023234	-.00271721	-.00487469	-.00287541	.00120267	-.00177113
$s(\hat{\gamma}_{MktRF})$	.08236616	.07104419	.07208958	.07775345	.08835816	.07548718	.07573175	.08641655
$t(\bar{\hat{\gamma}}_{MktRF})$	-.98735503	-.31433527	-.07572173	-.82105703	-.97449135	-.67282784	.28050752	-.36201929
$p(\bar{\hat{\gamma}}_{MktRF})$	.32390199	.7533854	.93966797	.41196887	.33056998	.50155644	.77927466	.71758347
$\bar{\hat{\gamma}}_{SMB}$	.00409447	.00720023	.00539267	.00552575	.00428972	.00864665	.00644662	.00619986
$s(\bar{\hat{\gamma}}_{SMB})$	.04674369	.04470702	.05305014	.05325647	.05066661	.05012781	.05914319	.06126536
$t(\bar{\hat{\gamma}}_{SMB})$	2.0579941	3.7839039	2.3882876	2.4377447	1.4954924	3.046816	1.925327	1.7874923
$p(\bar{\hat{\gamma}}_{SMB})$	.0400605	.0001713	.01726283	.01509432	.13580001	.00251097	.05510015	.07483159
$\bar{\hat{\gamma}}_{HML}$	.00142829	.0041045	.00557743	.00300047	.00286523	.00474323	.00513358	.0035023
$s(\bar{\hat{\gamma}}_{HML})$	.05078033	.04608861	.04581954	.04684913	.04922058	.04938041	.04770625	.04821779
$t(\bar{\hat{\gamma}}_{HML})$	.66083058	2.0923591	2.8599122	1.5047271	1.0282296	1.6966674	1.9007386	1.2829892
$p(\bar{\hat{\gamma}}_{HML})$	.50899716	.03686337	.00439821	.13296724	.30464085	.09076013	.05826065	.20045115
$\bar{\hat{\gamma}}_{RMW}$	-.0005988	-.00237976	-.00129798	-.00130885	-.00054696	-.00300515	-.00277919	-.00353555
$s(\bar{\hat{\gamma}}_{RMW})$	.03418063	.03508827	.03493891	.03907069	.03446101	.0376821	.03477392	.04345821
$t(\bar{\hat{\gamma}}_{RMW})$	-.41159312	-1.5934598	-.87282461	-.78706355	-.2803515	-1.4086683	-1.4116967	-1.4370198
$p(\bar{\hat{\gamma}}_{RMW})$	.68079773	.11163053	.38313888	.43158306	.77939423	.15993223	.159039	.15171763
$\bar{\hat{\gamma}}_{CMA}$	.00090204	.00158967	.0032204	.00248742	.00173257	.00005845	.00257138	.00305447
$s(\bar{\hat{\gamma}}_{CMA})$	.03486701	.03373501	.03264476	.03265369	.03450701	.03116389	.03291717	.03225852
$t(\bar{\hat{\gamma}}_{CMA})$	.60782698	1.1071247	2.3177477	1.7897218	.88687376	.03312848	1.3798154	1.6725115
$p(\bar{\hat{\gamma}}_{CMA})$	.54355267	.26872311	.02082843	.07404768	.37583217	.97359338	.16863466	.09542914
$\bar{\hat{\gamma}}_0$	.00678419	.0034867	.00448349	.00855333	.00928086	.00619494	.00405184	.01106588
$s(\bar{\hat{\gamma}}_0)$	.0877035	.07169449	.07078767	.08952423	.09608962	.07092823	.07036535	.09532762
$t(\bar{\hat{\gamma}}_0)$	1.8173999	1.1426102	1.4880876	2.2447303	1.7060394	1.5427487	1.0171174	2.0504287
$p(\bar{\hat{\gamma}}_0)$	.06969892	.25369671	.13729986	.0251814	.08899908	.12390865	.30988819	.04116055

IV. Figures

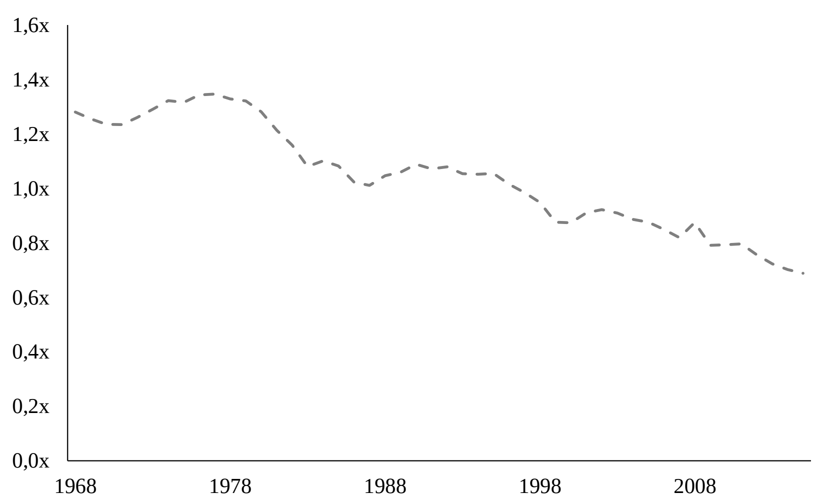
The graphs below are used in the discussion section of this paper. It includes the relevant figures of the average of all firms for the fiscal year ending 1968 to 2015, the development over time for each of the four AT percentiles considered and lastly, the same AT percentiles but rebased to fiscal year ending 1968. The graphs depict performance metrics which are AT, profit margin and ROA.

The data include all non-financial American listed companies on the NASDAQ, NYSE or Amex stock exchanges with fundamental data available for any fiscal year within the time period 1968 to 2015. The data set includes both active and inactive companies. For illustrative purposes, the AT percentile graphs also depict the data excluding outliers at the 1% and 99% level. Otherwise, all firms are included in the figures.

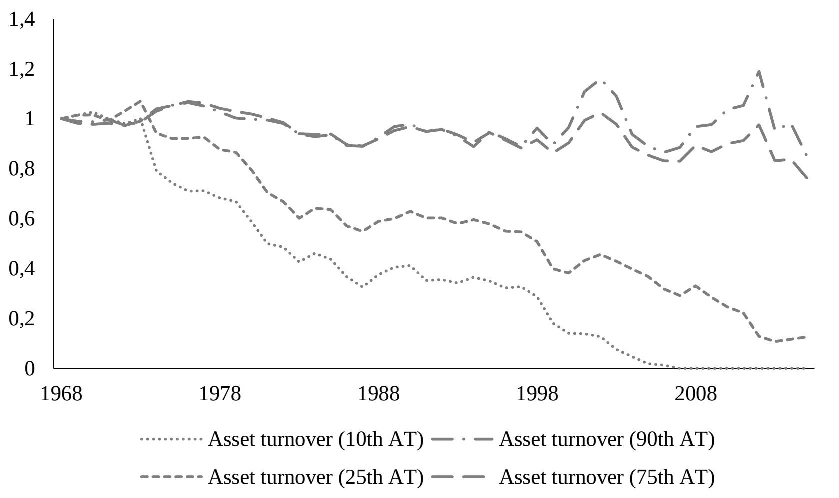
1. Asset turnover (AT)

The variable is defined as net sales divided by total assets at the end of each fiscal year. The average is a simple equal-weighted average calculated for each year during the time period considered.

Average AT of all firms (2)



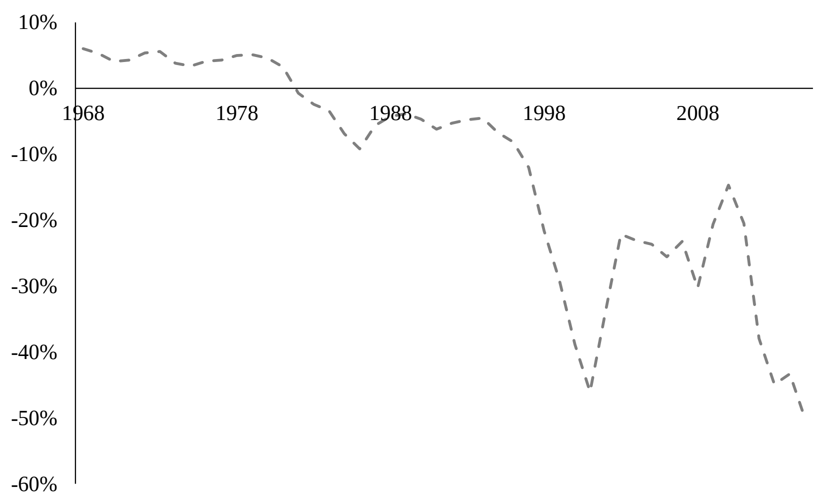
Rebased AT for relevant AT percentile (all firms) (3)



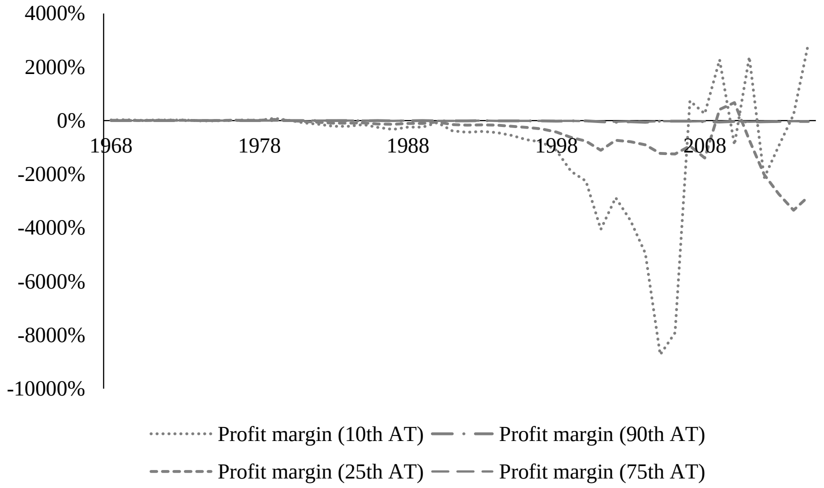
2. Profit margin

The profit margin is defined as net income at the end of the fiscal year divided by net sales for the same fiscal year. The average is a simple equal-weighted average calculated for each year during the time period considered.

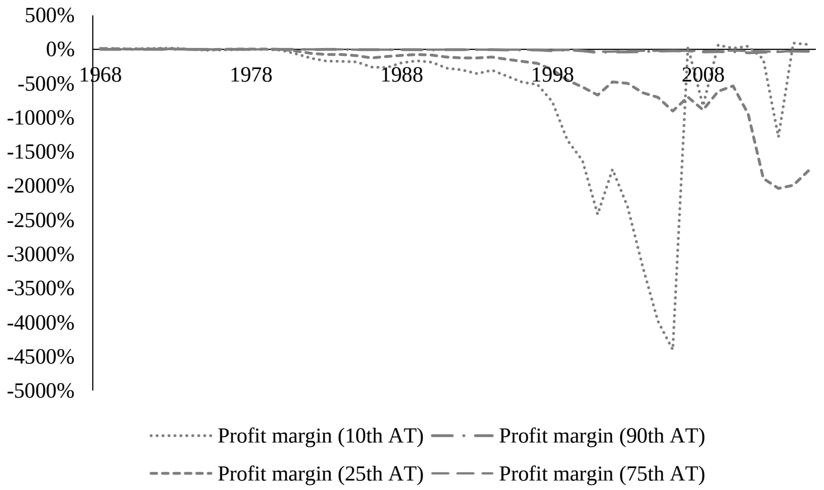
Average profit margin of all firms (4)



Profit margin for relevant AT percentiles (all firms) (5)



Profit margin for relevant AT percentiles (excluding outliers) (6)

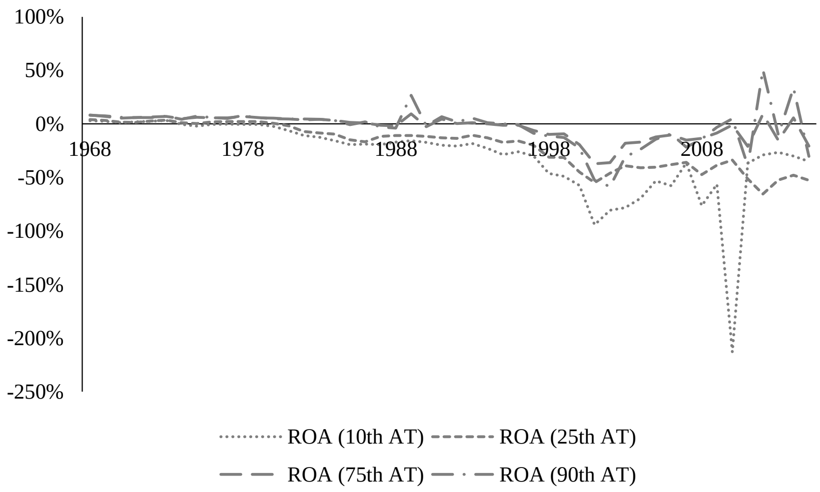


3. ROA

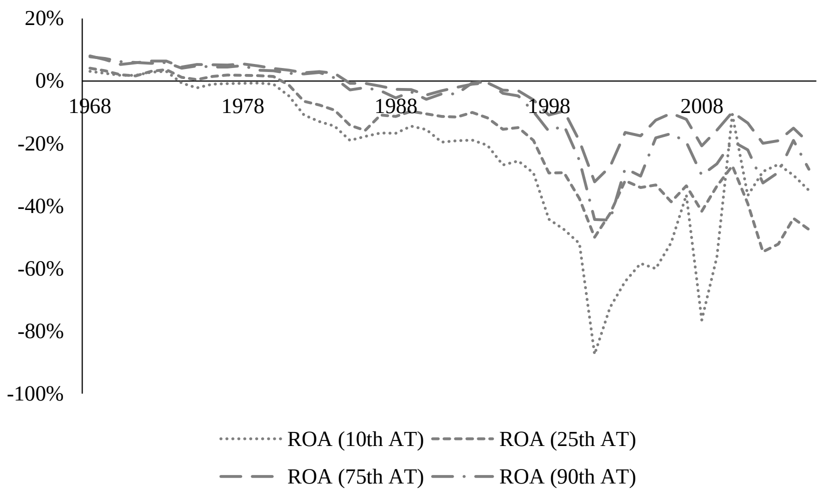
The variable is defined as the AT ratio for each individual firm at the end of each fiscal year times the profit margin at the end of the same fiscal year. The average is a simple equal-weighted average calculated for each year during the time period considered.

Average ROA of all firms (7)

ROA for relevant AT percentiles (all firms) (8)



ROA for relevant AT percentiles (excluding outliers) (9)



4. Additional graphs

Average sales development of all firms (10)