Aarhus University | Business and Social Sciences

Department of Economics and Business Economics

5362: Empirical Asset Pricing

Investment Distortions: Sorting Out the Winners and Losers

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Supervisor: Mads Markvart Kjær

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Abstract

This study investigates the relationship between investment distortion and stock performance using a sample of publicly traded U.S. firms from 1965 up to the end of 2019. The primary hypothesis posits that firms with low investment distortion, assumed to have more efficient capital allocation, would exhibit better stock performance than those with high investment distortion. However, the empirical findings reveal no significant outperformance associated with low investment distortion. Instead, the results highlight the importance of considering industry-specific factors and firm size when analyzing the relationship between investment distortion and stock performance. Further research is necessary to establish the robustness and generalizability of these findings.

Contents

1 Introduction

The efficient allocation of capital is a central tenet of modern finance theory and a critical determinant of firm performance and economic growth. Investment distortion, defined as the deviation from optimal investment behavior, can have profound implications for individual firms, industries, and the broader economy.

This paper examines the relationship between investment distortion and stock returns, aiming to contribute to the growing body of literature on the subject. The study is motivated by the potential implications of investment distortion for firm performance and the complex relationship between investment distortion and stock performance.

The primary hypothesis investigated in this paper is that firms with low investment distortion, which are assumed to have more efficient capital allocation, will exhibit better stock performance than firms with high investment distortion. The analysis is conducted using a sample of publicly traded U.S. firms from the period 1990 up to the end of 2019 and employs a portfolio sorting methodology to investigate the relationship between investment distortion and stock returns.

The paper is organized as follows: Chapter 2 provides a review of the relevant literature on investment distortion and stock performance, highlighting previous empirical findings and theoretical arguments that inform the hypothesis of this study. Chapter 3 describes the data sources, variables, and methodology employed in the analysis, including the construction of the Investment Distortion Index. Chapter 4 presents the empirical findings of the study, including results from the univariate portfolio sorting and the dependent sort based on size and investment distortion. Chapter 5 concludes the paper, summarizing the main findings and outlining avenues for future research.

The findings of this paper underscore the need for a more comprehensive understanding of the relationship between investment distortion and stock performance. While the initial results do not indicate a significant risk-adjusted premium associated with low investment distortion, further analysis reveals that certain portfolio combinations may yield significant outperformance. The results emphasize the importance of considering industry-specific factors, firm size, and alternative hypotheses in future studies to further examine the role of investment distortion in driving stock performance.

Literature Review

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This chapter is divided into two main sections. The first section provides a review of the existing literature, summarizing the key findings and insights from previous research on portfolio construction, risk factors, and investment strategies. The second section identifies gaps in the current body of knowledge and proposes a new hypothesis to address some of these shortcomings.

2.1 Existing Literature

Tobin's Q, introduced by Tobin (1969), measures firm valuation as the ratio of a firm's market value to its asset replacement cost. A higher Tobin's Q suggests a firm is more likely to invest in new projects. Fama and French (1993) found that firms with high book-to-market ratios tend to have higher average stock returns, implying a link between investment behavior and stock performance. Asker et al. (2014) found that listed firms invest less and have lower Tobin's Q than private counterparts, attributing this to potential distortions from stock market listing.

Whited and Wu (2006) showed that financially constrained firms typically have lower investment rates and higher stock returns, suggesting riskier firms require higher returns. Cooper and Ejarque (2003) found that financial frictions can lead to over- or under-investment in capital, affecting firms' performance and valuation. Titman et al. (2004) documented a negative association between capital investments and stock returns, suggesting higher required returns for firms with higher investment rates.

Brown et al. (2009) discovered that R&D-intensive firms have higher growth rates, especially during the 1990s R&D boom. This aligns with Eberhart et al. (2004) and Aghion et al. (2004), who showed that innovative firms have different financial structures and higher equity financing reliance.

Stambaugh and Yuan (2016) developed mispricing factors that capture cross-sectional return anomalies and found that they are related to investment, profitability, and value factors.

In their comparison of different factor models, Hou et al. (2018) discovered that the investment factor (CMA) and the profitability factor (RMW) from Fama and

French (2015) are helpful in explaining stock returns. The CMA factor is derived by calculating the difference in returns between firms with low and high investment-to-capital ratios. This factor highlights the tendency of conservative firms (those with low investment-to-capital ratios) to have higher returns than aggressive firms (those with high investment-to-capital ratios). The authors contend that the CMA factor is a significant predictor of stock returns and effectively accounts for the cross-section of expected returns.

2.2 Expanding the Horizon

The existing literature on investment behavior still leaves a gap in understanding the relationship between the inability to adapt investments and stock returns. This inability is proxied by investment distortions, defined as residuals from a regression of the Investment-to-Capital ratio on variables such as lagged Investment-to-Capital ratio, Tobin's Q, R&D intensity, Free Cash Flow, yearly revenue growth, leverage, and profitability. The detailed methodology is described in Section 3.2.1. In contrast, the CMA-factor in Fama and French (2015) focuses on the level of investment-to-capital ratios, without accounting for deviations from expected investments.

This paper sorts firms into portfolios based on investment distortions, whereas the CMA-factor is constructed by taking the difference in returns between firms with low and high investment-to-capital ratios. The methods for portfolio formation are fundamentally different: this study emphasizes deviations from expected investments, while the CMA-factor considers the level of investment-to-capital ratios.

3 Data and Methodology

In this section, I describe the data sources and methodology used to sort firms based on investment distortion and investigate the relationship between investment distortion and stock returns.

3.1 Data

The primary data sources for this study are the Center for Research in Security Prices (CRSP) and Compustat Fundamentals through Wharton Research Data Services (WRDS). CRSP provides comprehensive historical stock market data, including stock returns, market capitalizations, and trading volumes. Compustat Fundamentals offers firm-level financial statement data, such as investment, revenue, and R&D expenditures. By combining these two data sources, we construct a comprehensive dataset of firm-level characteristics and stock returns.

The CRSP and Compustat datasets are cleaned to remove any outliers, missing values, and data inconsistencies. This step ensures that the analysis is based on accurate and reliable data, and above all, replicability of the results.

Tab. 3.1.: Descriptive Statistics of Excess Monthly Returns.

exchange	mean	sd	min	median	max	n
AMEX	0.011	0.174	-0.828	-0.006	6.403	26770
NASDAQ	0.009	0.186	-0.956	-0.004	8.747	109774
NYSE	0.014	0.110	-0.879	0.008	2.750	70065

n refers to the number of observations in the sample.

The sample period analyzed in this study spans from 1965 up to the end of 2019, encompassing a diverse set of economic environments and financial market conditions. Over these 54 years, the global economy has experienced numerous cycles of growth and contraction, including significant events such as the oil crises in the 1970s, the stock market crash of 1987, the dot-com bubble in the late 1990s, and the Global Financial Crisis in 2007-2008, and ending just before COVID-19 pandemic in 2020. The sample period also captures various monetary and fiscal policy changes, technological advancements, and shifts in industry dynamics.

Analyzing this extensive time frame allows us to explore the relationship between investment distortion and stock returns across different market conditions, providing a of the factors that drive the observed patterns and enabling us to identify potential robustness of our findings.

In light of the underrepresentation of AMEX and NASDAQ stocks in the sample, as shown in Table 3.1, it is deemed most appropriate to focus solely on NYSE-listed firms for the analysis. NYSE-listed firms typically have higher disclosure requirements and more stringent listing standards. This results in more reliable and accurate financial data, which aims to enhance the quality of the analysis.

3.2 Methodology

3.2.1 Investment Distortions

Investment distortion is defined as the absolute value of the residuals from a regression of the Investment-to-Capital ratio on lagged Investment-to-Capital ratio, Tobin's Q, R&D intensity, Free Cash Flow, yearly revenue growth, leverage, and profitability. Consider

$$
\begin{aligned}
\frac{\text{Investment}}{\text{Capital}}_{i,t} &= \alpha_{i,0} + \alpha_{i,1}\frac{\text{Investment}}{\text{Capital}}_{i,t-1} + \alpha_{i,2}\text{Tobin's Q}_{i,t} \\
&+ \alpha_{i,3}\frac{\text{Capital Expenditure}_{i,t}}{\text{Assets}_{i,t-1}} + \alpha_{i,4}\text{Free Cash Flow}_{i,t} \\
&+ \alpha_{i,5}\left[\log\left(\text{Revenue}_{i,t}\right) - \log\left(\text{Revenue}_{i,t-1}\right)\right] \\
&+ \alpha_{i,6}\frac{\text{Debt}}{\text{Assets}}_{i,t} + \alpha_{i,7}\frac{\text{Net income}}{\text{Assets}}_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

Tab. 3.2.: Descriptive Statistics of Investment Distortion.

exchange	mean	sd	min	median	max	n
NYSE	0.068	0.473	0	0.018	41.67	70065

Investment Distortion is computed as in equation 3.1. n refers to the number of observations in the sample.

Then conversely

$$\begin{aligned}\varepsilon_{i,t} = \frac{\text{Investment}}{\text{Capital}}_{i,t} - \Bigg[\alpha_{i,0} + \alpha_{i,1}\frac{\text{Investment}}{\text{Capital}}_{i,t-1} + \alpha_{i,2}\text{Tobin's Q}_{i,t} \\ + \alpha_{i,3}\frac{\text{Capital Expenditure}_{i,t}}{\text{Assets}_{i,t-1}} + \alpha_{i,4}\text{Free Cash Flow}_{i,t} \\ + \alpha_{i,5}\left[\log\left(\text{Revenue}_{i,t}\right) - \log\left(\text{Revenue}_{i,t-1}\right)\right] \\ + \alpha_{i,6}\frac{\text{Debt}}{\text{Assets}}_{i,t} + \alpha_{i,7}\frac{\text{Net income}}{\text{Assets}}_{i,t}\Bigg].\end{aligned}$$

This then allow us to define

$$\text{Investment Distortion}_{i,t} = |\varepsilon_{i,t}| \tag{3.1}$$

for firm $i = 1, ..., N$ and time $t = 1, ..., T$.

Incorporating the lagged investment-to-capital ratio accounts for persistent investment decisions and a firm's capital structure. As argued by S. M. Fazzari et al. (1988), this variable controls for historical investment behavior and its impact on future decisions.

R&D intensity measures a firm's commitment to research and development relative to revenues, indicating innovation and long-term growth focus (Chan et al. (2001)). It helps control for investment in intangible assets, which may have different financing and risk-return characteristics.

Revenue growth captures a firm's ability to expand operations and market share. S. Fazzari et al. (2000) argue that higher growth may indicate more promising investment opportunities, with different investment patterns than lower-growth firms.

Tobin's Q (Tobin (1969)) represents market valuation of a firm's investment opportunities. A higher Q indicates more favorable market valuation, helping control for market perceptions and their impact on investment distortions.

Free cash flow controls for a firm's financial flexibility and its ability to invest or return cash to shareholders (Jensen (1986)).

Leverage captures reliance on debt financing, and Titman et al. (2004) argue that higher leverage may indicate greater financial risk, influencing investment decisions.

Profitability measures a firm's operational efficiency and ability to generate returns. More profitable firms may exhibit different investment behaviors than less profitable ones (Fama and French (2015)), controlling for financial performance and potential influence on investment distortions.

These variables provide a comprehensive list of key factors that could impact investment distortions. Together, they capture the firm's financial performance, growth prospects, market valuation, and capital structure. While other variables could potentially be included, these seven factors are widely recognized in the literature and should provide a robust and comprehensive framework for analyzing investment distortions.

This paper tests the hypothesis of a premium for firms with low investment distortion and lower returns for firms with high investment distortion for the following reasons:

- Efficient Capital Allocation: Firms with low investment distortion may allocate capital more efficiently, leading to higher profitability and returns as pointed out by Titman et al. (2004) and Brown et al. (2009). In contrast, high investment distortion may indicate misallocation of capital or overinvestment, which can negatively impact firm value and subsequently returns as evident in Cooper and Ejarque (2003) and Asker et al. (2014).
- Financial Constraints and Agency Issues: Whited and Wu (2006) argue that low investment distortion may signal the absence of financial constraints and agency problems, which are associated with better stock performance, as seen in Aghion et al. (2004). In turn, S. M. Fazzari et al. (1988) points to large deviations from optimal investment suggesting the presence of financial constraints or agency conflicts, leading to suboptimal investment decisions and, again, lower stock returns as described in Jensen (1986).
- Risk-Adjusted Premium: Firms with low investment distortion may exhibit a risk-adjusted premium due to their more efficient capital allocation and better operating performance (Titman et al. (2004)). In contrast, firms with high investment distortion may carry higher risk related to poor investment decisions,

leading to lower risk-adjusted returns (Eberhart et al. (2004); Stambaugh and Yuan (2016)).

3.2.2 Portfolio Sorting

This study employs a portfolio sorting methodology to examine the relationship between investment distortion and stock returns. Initially, the sample is sorted solely based on investment distortion, investigating the entire sample, and the subsample excluding manufacturing firms.

By analyzing these different subsamples, we aim to identify any industry-specific effects that may arise from the presence of investment distortion. As evident from Figure A.1, the manufacturing industry accounts for a large amount of the overall Investment Distortion. Examining subsamples with and without manufacturing firms allows us to gain a deeper understanding of the relationship between investment distortion and stock returns while controlling for industry-specific effects, enhancing the robustness and generalizability of our findings.

Subsequently, the paper employs a conditional sorting procedure, where the sample is first sorted into three size groups, followed by sorting within each size group based on investment distortion. This two-step approach allows us to account for potential size-related influences on the relationship between investment distortion and stock returns. The conditional sorting is conducted across the subsample excluding manufacturing firms to maintain consistency with the initial sorting approach.

The portfolio sorting methodology employed in this study provides a robust framework for investigating the relationship between investment distortion and stock returns while considering the potential impact of industry and firm size. By conducting both unconditional and conditional sorts, the paper seeks to unveil any systematic patterns in stock performance that may be associated with investment distortion and understand the role of industry and size factors in shaping these patterns.

4 Empirical Findings

4.1 Univariate Portfolio Sorting

The analysis begins by sorting stocks into five portfolios based on investment distortion, from low to high. This univariate approach allows a direct assessment of the relationship between investment distortion and stock returns. However, potential limitations, such as omitted variable bias and other firm-specific factors, should be acknowledged.

Contrary to the initial hypothesis, negative alphas in Figure A.5 suggest that low investment distortion does not necessarily result in significantly higher stock returns. This highlights the complexity of the relationship and the importance of considering additional factors. The alphas are negative across the board, possibly due to inherent data limitations, as only firms with publicly available investment data are considered.

Figure A.3 shows the Long-Short (Low - High) portfolio under-performs relative to the market, but the estimated alpha from a regression on the Fama French 5-factor model in Table 4.1 is not significantly different from zero. Notably, the beta of the Long-Short portfolio is zero, suggesting no systematic market exposure.

Tab. 4.1.: Significance test of Fama and French (2015) α from Long-Short Portfolio.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.002	0.003	0.932	0.352

Long-Short Portfolio is long on low Investment Distortion firms and short on high Investment Distortion firms (Portfolio 1 - Portfolio 5 from Figure A.5). The test is based on monthly returns and Newey-West errors.

Industry Distribution and Manufacturing Industry

A closer examination of the industry distribution within the Low and High portfolios reveals that the Manufacturing industry accounts for a large proportion of the portfolio as seen in Figure A.4.

Further analysis of investment distortion by industry indicates that the Manufacturing industry is an outlier in terms of the magnitude of investment distortion, for instance Figure A.1 reveals the manufacturing industry consistently exhibits higher investment distortion.

This observation raises questions about the potential influence of industry-specific factors and motivates the exclusion of the Manufacturing industry from the sample.

The Manufacturing industry accounts for a large portion of both portfolios and exhibits higher investment distortion compared to other industries, likely due to the capital-intensive nature of the sector. Manufacturing firms often require substantial investments in machinery, equipment, and facilities to maintain or expand their production capabilities.

Consequently, these firms may have a higher propensity for deviations from optimal investment behavior as they face more complex and dynamic investment decisions. This scenario could lead to higher investment distortion in the Manufacturing industry compared to other less capital-intensive sectors, prompting the need to analyze its influence separately.

4.1.1 Excluding Manufacturing Industry

Upon excluding the Manufacturing industry and re-sorting the portfolios, the Low portfolio exhibits a negative alpha, while the High portfolio has a non-significant alpha as evident in Figure A.8. Nonetheless we continue the analysis of the hypothesis.

The Long-Short (Low - High) portfolio underperforms the market; however, the estimated alpha from a regression on the Fama French 5-factor model is not statistically significant as seen in Table 4.2.

Tab. 4.2.: Significance test of Fama and French (2015) α from Long-Short Portfolio (excluding manufacturing firms).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.003	0.004	-0.775	0.439

Long-Short Portfolio is long on low Investment Distortion firms and short on high Investment Distortion firms. The t-test is based on monthly returns.

The beta of the Long-Short portfolio remains zero, indicating that the portfolio is not exposed to systematic market risk.

4.2 Dependent Sort: Size and Investment Distortion

Incorporating market capitalization into the analysis through a dependent sort based on size and investment distortion provides a more nuanced understanding of the relationship between investment distortion and stock returns. By controlling for the potential confounding effects of firm size, this approach allows for a more accurate assessment of the role of investment distortion in driving stock performance.

To further refine the analysis, market capitalization is incorporated by constructing portfolios based on a dependent sort: first on size (small, medium, large) and then on investment distortion (low, medium, high).

The Patton and Timmermann (2010) Test for Monotonicity is employed to test for monotonicity. The test investigates the presence of monotonic patterns in expected returns based on a specific sorting criterion, in this case size and investment distortion. The test helps to assess whether the empirical evidence supports the hypothesized relationship in the data. The test results are presented in Table 4.3.

Tab. 4.3.: Patton and Timmermann (2010) Test for Monotonicity.

low minus high	Up	Down	MR^{all}	Wolak	Bonferroni
0.022	0	0.864	0.728	0.084	0.572

The first column presents the difference in the estimated expected returns between the lowest and highest ranked portfolios. The second and third columns show the percentage of null hypothesis rejections, which state that there is no relation, in favor of the alternative hypothesis that the sum of positive (Up) or the absolute values of negative (Down) differences in expected returns is not zero. The fourth column displays the percentage of rejections using the MR test, which considers all possible inequalities implied by monotonicity (MR^{all}). The fifth and sixth columns (Wolak and Bonferroni) present the percentage of rejections of the null hypothesis of a weakly monotonic relation using the test proposed by Wolak (1989), with critical values derived from one thousand simulations per replication, and a Bonferroni bound test. Columns two to four are based on the stationary bootstrap method and employ one thousand bootstrap replications.

Consistent with the results from the univariate approach, the Wolak test rejected the null that expected returns follow a monotonic pattern in both size and Investment Distortion. In contrast, the more conservative Bonferroni test failed to reject the null hypothesis of weak monotonicity. To summarize, two-way sorts can be used to diagnose why empirical evidence could fail to support a hypothesized pattern in expected returns. Here the findings suggest that the size effect in expected returns is absent from growth firms and among loser stocks. Moreover, Investment Distortion effects seem strong for large and medium-size firms but not among the smallest quintile of stocks with an estimated α not significantly difference from zero in low and medium Investment Distortion portfolios.

4.3 Implications

In summary, the empirical findings from the analyses of univariate portfolio sorting, as well as the dependent sort based on size and investment distortion, provide nuanced insights into the relationship between deviation from optimal investment behavior and stock returns.

While the initial results show no significant risk-adjusted premium associated with low investment distortion, further analysis excluding the Manufacturing industry and incorporating market capitalization indicates that certain portfolio combinations may yield significant outperformance.

These results highlight the importance of considering industry-specific factors and firm size in examining the relationship between investment distortion and stock performance. The findings also underscore the need for robustness checks and sensitivity analyses to identify potential drivers of the observed patterns.

Nevertheless, these results should be interpreted with caution, and further research is necessary to establish the robustness and generalizability of the findings. Future studies may consider exploring additional control variables, alternative measures of investment distortion, or extending the analysis to different markets and time periods.

5 Concluding Remarks

This paper focused on the hypothesis that firms with low investment distortion exhibit better stock performance. However, one could also consider the alternative hypothesis: firms with high investment distortion might show better stock performance due to:

- Growth Opportunities: High investment distortion firms may invest heavily in growth opportunities, potentially leading to higher future profitability and stock returns, as discussed in Chan et al. (2001).
- Market Expectations and Risk Compensation: Investors may place a premium on high investment distortion firms due to perceived growth potential, resulting in higher stock valuations and returns, as supported by Asker et al. (2014) and Hou et al. (2018).
- Competitive Advantage: High investment distortion firms may strategically invest in areas creating competitive advantages, leading to higher market share, profitability, and stock returns, as noted by Barney et al. (2001) and Peteraf (1993).

These arguments are not mutually exclusive with those presented in section 3.2.1. The relationship between investment distortion and stock performance could be influenced by a combination of these factors. If high investment distortions indicate growth opportunities, the analysis should consider different re-balancing periods to account for various investment horizons. Further empirical analysis is needed to determine dominant drivers of stock returns for high and low investment distortion firms.

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Figures

Fig. A.1.: Investment Distortion by Industry

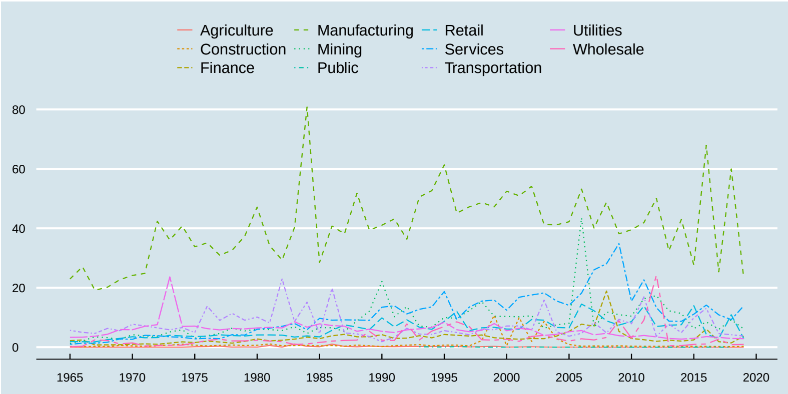


Fig. A.2.: Market Cap Weighted Average of Variables

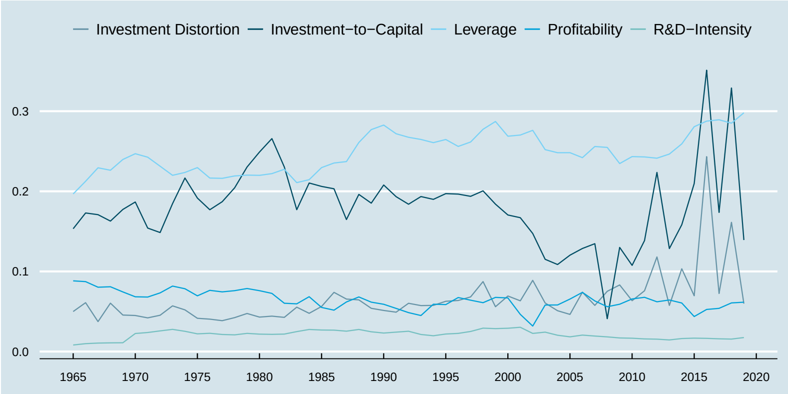
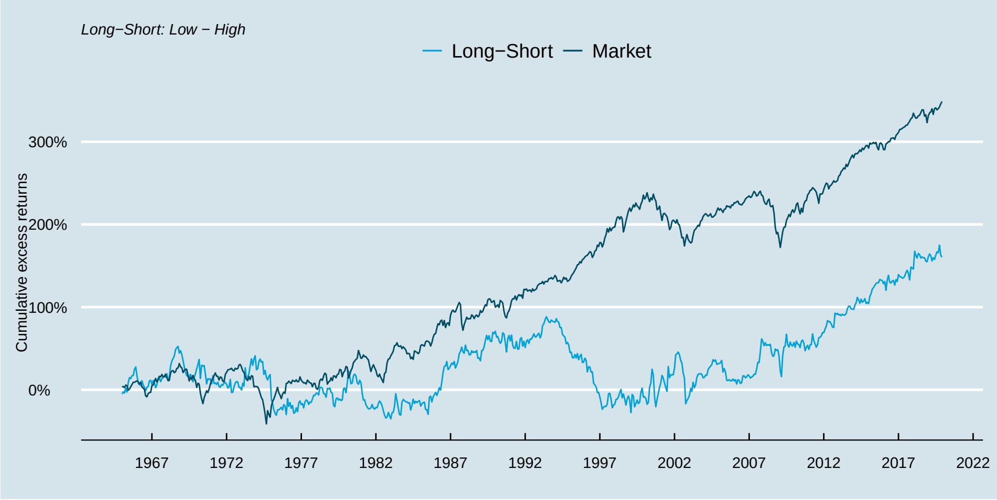


Fig. A.3.: Long-Short vs. Market



Long-Short Portfolio is long on low Investment Distortion firms and short on high Investment Distortion firms.

Fig. A.4.: Industry distribution in High and Low Portfolio

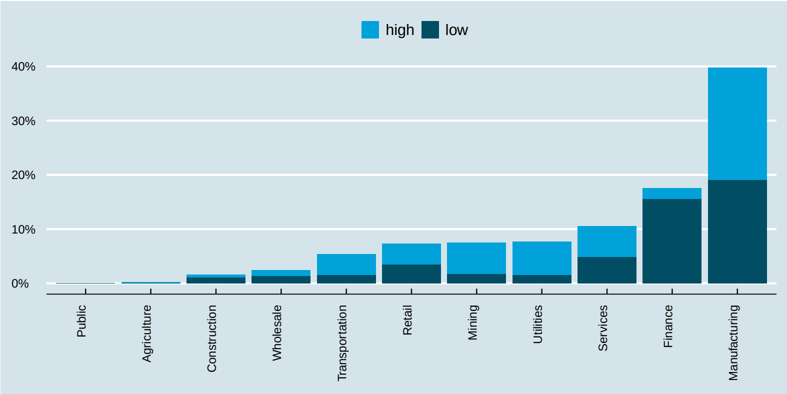
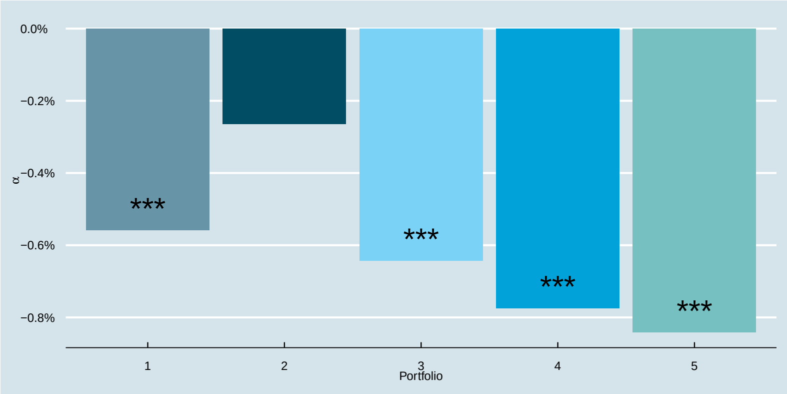


Fig. A.5.: Fama and French (2015) α of Distortion-sorted Portfolios



Note: *** indicates a p-value less than 0.01, ** less than 0.05, and * less than 0.1.

Fig. A.6.: Fama and French (2015) β_{mkt} of Distortion-sorted Portfolios

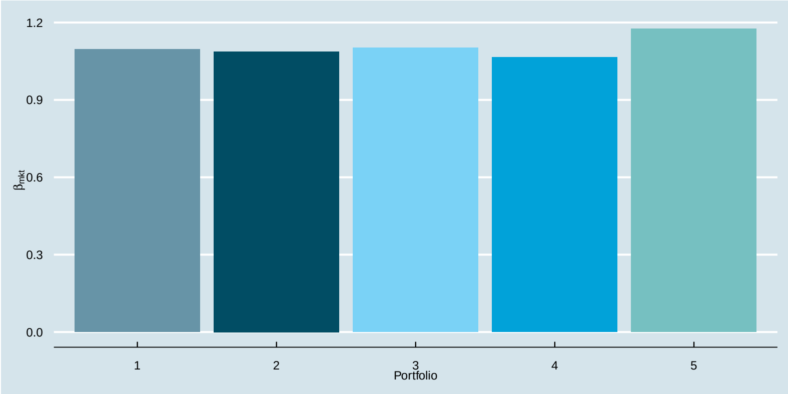


Fig. A.7.: Fama and French (2015) β_{cma} of Distortion-sorted Portfolios

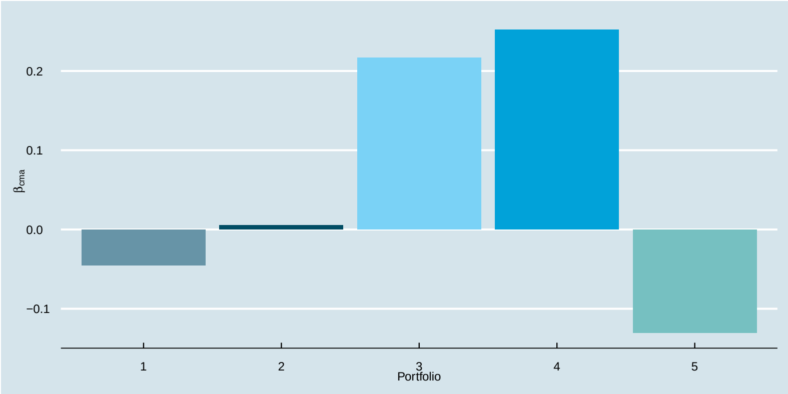
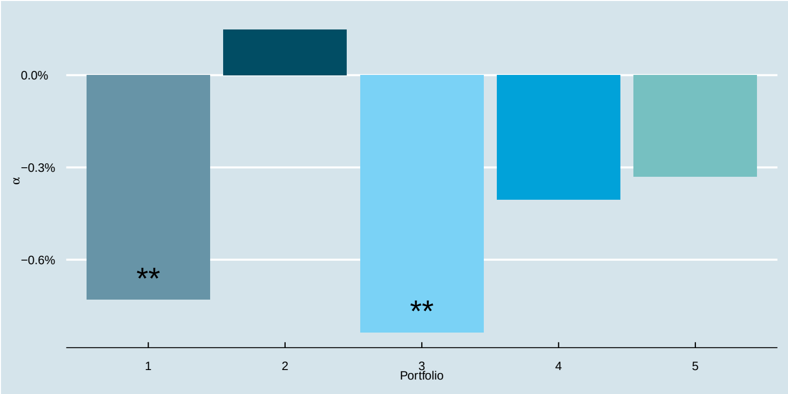


Fig. A.8.: Fama and French (2015) α of Distortion-sorted Portfolios (ex. Manufacturing)



Note: *** indicates a p-value less than 0.01, ** less than 0.05, and * less than 0.1.

Fig. A.9.: Fama and French (2015) β_{mkt} of Distortion-sorted Portfolios (ex. Manufacturing)

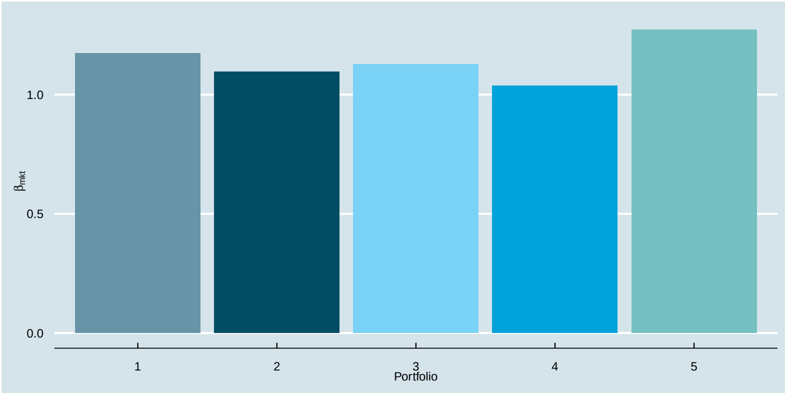


Fig. A.10.: Fama and French (2015) β_{cma} of Distortion-sorted Portfolios (ex. Manufacturing)

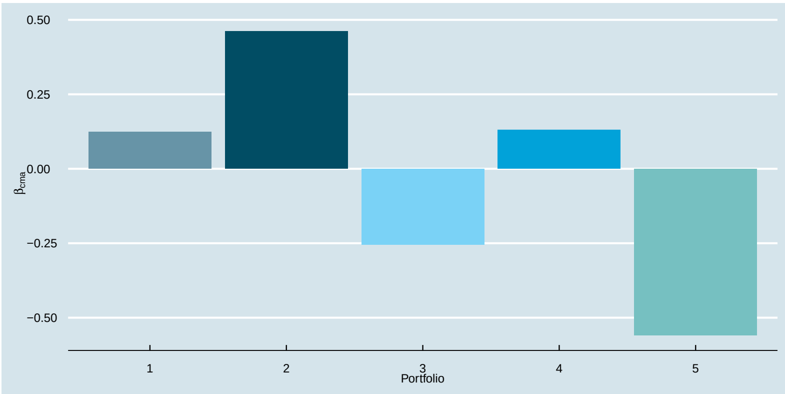
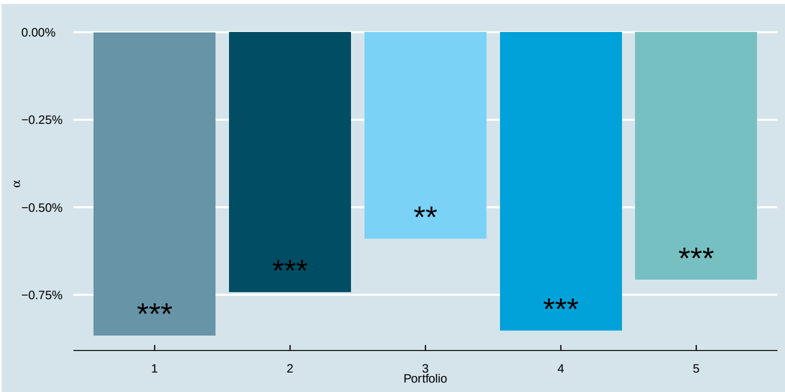


Fig. A.11.: Fama and French (2015) α of Distortion-sorted Portfolios (Manufacturing)



Note: *** indicates a p-value less than 0.01, ** less than 0.05, and * less than 0.1.

Fig. A.12.: Fama and French (2015) β_{mkt} of Distortion-sorted Portfolios (Manufacturing)

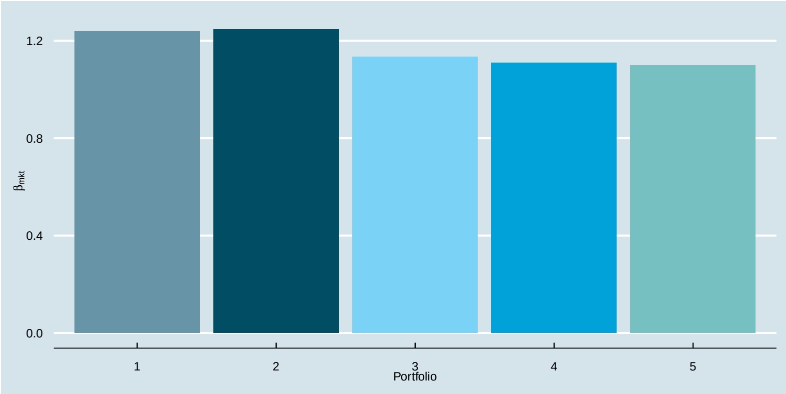


Fig. A.13.: Fama and French (2015) β_{cma} of Distortion-sorted Portfolios (Manufacturing)

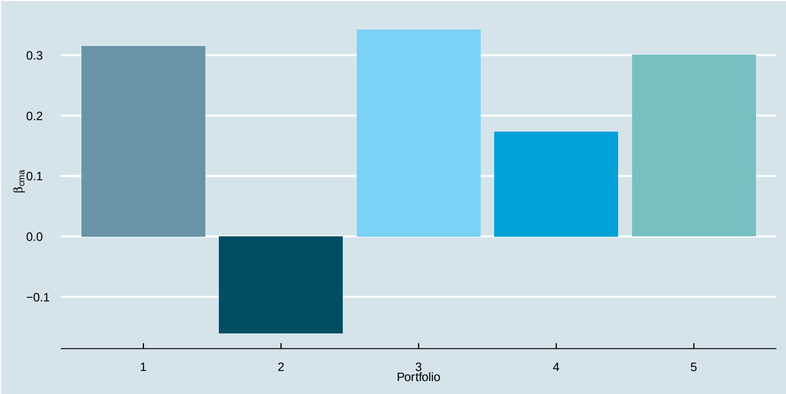


Fig. A.14.: Long-Short vs. Market (ex. Manufacturing)

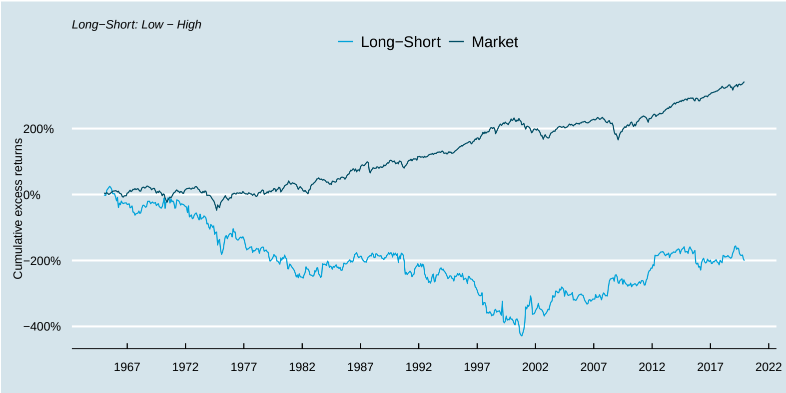


Fig. A.15.: Long-Short vs. Market (Manufacturing)

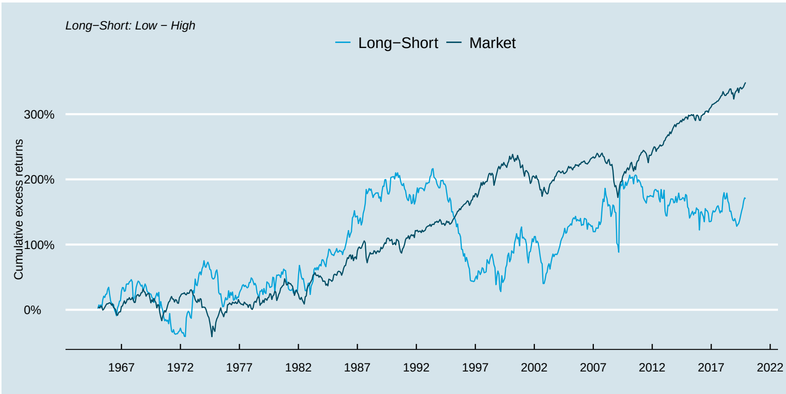
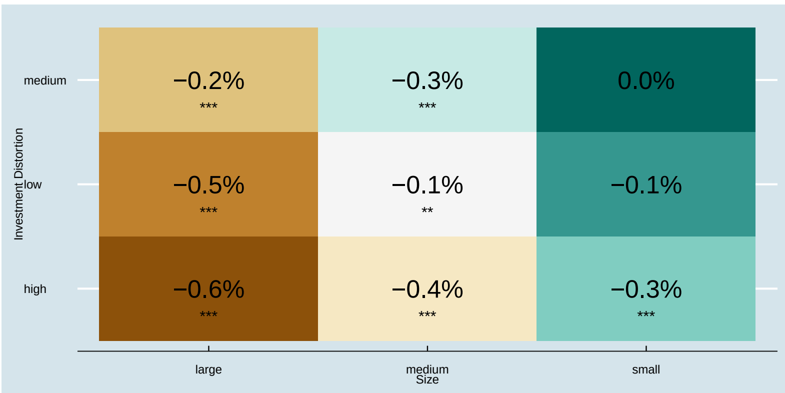


Fig. A.16.: Fama and French (2015) α of Size and Investment Distortion sorted Portfolios



Note: *** indicates a p-value less than 0.01, ** less than 0.05, and * less than 0.1.