UNIVERSIDADE CATÓLICA PORTUGUESA

Does Industry Concentration Explain the Profits of the Investment Strategy?

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Abstract

This dissertation investigates the role of industry concentration in explaining the profitability of the Conservative Minus Aggressive (CMA) investment strategy. While previous studies have established the return premium associated with conservative investment policies, the economic mechanisms driving the CMA strategy remain underexplored. This study builds upon the work of Moskowitz & Grinblatt (1999) on industry momentum and extends their framework to assess the impact of industry concentration on investment strategy returns. The analysis examines whether industry dynamics explain CMA profits by replicating and expanding their methodology. This study applies multiple portfolio sorting techniques to isolate industry effects. The findings indicate that industry concentration does not significantly explain investment-based returns, confirming that it is not the main driver of CMA profitability.

Keywords: Industry Concentration, Investment Strategy, Profitability

Resumo

Esta dissertação investiga se a concentração industrial desempenha um papel significativo na explicação da rentabilidade da estratégia de investimento Conservative Minus Aggressive (CMA). Embora pesquisas anteriores tenham estabelecido o prémio de retorno associado a políticas de investimento conservadoras, os mecanismos económicos subjacentes à estratégia CMA ainda não foram suficientemente explorados. Este estudo baseia-se no trabalho de Moskowitz & Grinblatt (1999) sobre o Momentum da indústria e expande o seu modelo para avaliar o impacto da concentração industrial nos retornos das estratégias de investimento. Através da replicação e ampliação da sua metodologia, a análise investiga se os lucros da CMA são impulsionados por dinâmicas industriais. Para tal, são aplicadas diversas técnicas de ordenação de portfólios com o objetivo de isolar os efeitos da indústria. Os resultados indicam que a concentração industrial não explica de forma significativa os retornos baseados em investimento, confirmando que não é um fator determinante na rentabilidade da estratégia de CMA.

Palavras-chave: Concentração Industrial, Estratégia de Investimento, Rentabilidade

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Chapter 1
Introduction

Understanding the determinants of stock returns has long been a key focus in asset pricing research. Over time, the development of factor models, from the Capital Asset Pricing Model (CAPM) to the Fama-French Five-Factor Model (FF5F), has provided increasingly refined tools to explain cross-sectional differences in stock returns. One of the components of the FF5F is the Conservative Minus Aggressive (CMA) factor, which captures the return premium associated with firms' investment behaviour.

This dissertation analyses a CMA-type strategy that mirrors the logic of the CMA factor but differs in construction. Specifically, firms are annually sorted into deciles based on their asset growth from year *t–2* to *t–1*. This strategy measures the return spread between low-asset-growth firms (conservative investors, bottom decile) and high-asset-growth firms (aggressive investors, top decile).

While previous studies have confirmed that conservative firms tend to outperform aggressive ones, the economic sources of this return premium are not yet fully understood. This dissertation seeks to fill this gap by examining whether industry concentration explains the cross-sectional variation in returns from the CMA-type strategy.

1.1. Motivation and Research Gap

A key motivation for this research is the ongoing debate regarding the true drivers of factor premiums in asset pricing models. Although previous studies (Titman et al., 2004; Cooper et al., 2008) have linked firm-level investment behaviour to future returns, the industry's role in explaining these patterns remains underexplored.

In particular, the work of Moskowitz & Grinblatt (1999) demonstrated that much of the profitability of momentum strategies is attributable to industry momentum rather than purely firm-level effects. This raises the question: could a similar pattern apply to investment strategies like CMA? Industries differ significantly in capital intensity, competition, and growth potential, which could influence investment behaviour and associated returns. Thus, it is crucial to test whether CMA returns are influenced more by industry trends or by other factors.

1.2. Research Question

As a result, this dissertation seeks to answer the following research question: **Does industry concentration explain the profitability of the investment strategy?**

To address this question, I investigate whether the CMA strategy's returns remain significant after controlling for industry effects, using methodologies that separate firm-specific investment policies from industry-wide investment trends.

1.3. Contribution and Originality

This dissertation contributes to the scientific knowledge in asset pricing by addressing the unexplored role of industry concentration in the profitability of the CMA strategy. By replicating and extending the results of Moskowitz & Grinblatt (1999) in the investment strategy context, this study provides new insights into whether CMA returns arise from firm-specific investment decisions or broader industry-level dynamics. Beyond its theoretical contributions, this research has practical implications for portfolio managers and investors who rely on factor-based strategies. Identifying potential industry-driven biases in the investment strategy's returns offers valuable guidance on whether industry effects should be accounted for in portfolio construction and risk management.

The originality of this study lies in applying the industry-momentum framework to the CMA strategy, an approach that has not been extensively explored. Leveraging long-term historical data and employing multiple empirical tests to isolate industry effects, this dissertation aims to provide a deeper and more rigorous understanding of how industry structure interacts with investment-based return premiums.

1.4. Overview of Empirical Findings

To ensure the robustness of the methodology, the research begins by replicating and extending the results of Moskowitz & Grinblatt (1999) in the context of momentum. The replication proved successful, aligning closely with the original study's results. The extension yielded consistent results and further reinforced that industry-level dynamics contribute to momentum strategy returns. This replication exercise serves as a methodological foundation for the primary focus of this dissertation: examining whether similar industry effects are present in the profitability of the CMA strategy.

To determine whether industry effects drive these returns, three distinct industry-adjusted methodologies are used:

1. **Industry-Neutral Test:** Portfolios are formed within industries, ensuring that comparisons are made among firms in the same industry.
2. **Excess Industry Return Test:** Each firm's return is adjusted by subtracting the average return of its industry, isolating firm-specific effects.
3. **High-Industry Losers Minus Low-Industry Winners Test:** This test compares the performance of firms in industries with high average strategy scores to those with low average scores, testing whether the strategy's profitability is concentrated at the industry level.

Accordingly, the same approach is applied to the CMA-type strategy. The first two tests showed positive and statistically significant returns. Moreover, the results lose statistical significance in the third test. This suggests that industry-level dynamics do not primarily drive the strategy's profitability.

1.5. Structure

The dissertation is structured as follows:

Chapter 1 introduces the research topic and outlines the dissertation's motivation, research gap, objectives, and structure.

Chapter 2 reviews the literature, focusing on the evolution of asset pricing models, emphasising the Fama-French Five-Factor Model (FF5F) and the CMA strategy. Additionally, it examines Moskowitz & Grinblatt (1999) study on industry momentum, comparing their original findings with my replication and extension and exploring how their insights can be applied to investment strategy.

Chapter 3 presents the data sources and variables used in the study. It details the data collection process and provides a comprehensive and statistical description of the key variables.

Chapter 4 presents the empirical analysis detailing the construction of the industry-neutral, excess-industry, and high-industry-losers vs. low-industry-winners portfolios. It explains the tests performed, reports the results and discusses their implications.

Chapter 5 concludes by summarising the key findings, exploring their implications for asset pricing theory, outlining the limitations encountered in this study, and providing recommendations for future research.

Chapter 2
Literature Review

In the financial world, there is significant interest in understanding the relationship between a factor's risk and its impact on returns and how they are valued in the market. Various models, known as asset pricing models, have been developed to comprehend this relationship.

2.1. Foundations of Asset Pricing

Markowitz (1952) designed the foundations for asset pricing models by introducing mean-variance optimisation in portfolio construction. His Modern Portfolio Theory (MPT) demonstrated that diversifying a portfolio reduces risk by considering the correlation between assets, not just individual risks. He also developed the efficient frontier concept, representing portfolios offering the best possible risk-return trade-off.

2.1.1. Capital Asset Pricing Model

The Capital Asset Pricing Model (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961) builds on Markowitz’s work and describes the relationship between systematic risk and expected asset returns. To CAPM, a security’s expected return is proportional to its beta, which measures sensitivity to market movements. Despite its simplicity and widespread use, CAPM has limitations, namely, the single-factor assumption. Empirical evidence shows that other factors, such as size, value, and momentum, also affect asset returns, leading to the development of multi-factor models. More recent models and approaches have been developed to address this limitation, such as APT and FF3F/FF5F.

2.1.2. Arbitrage Pricing Theory

Therefore, Ross (1976) presented the Arbitrage Pricing Theory (APT) as an alternative to CAPM. APT suggests that multiple macroeconomic factors, such as inflation, interest rates, and economic growth, drive asset returns. It allows for a more flexible structure in explaining returns through diversified exposure to several systematic risks.

2.1.3. Fama-French Factor Models

The Fama French Three-Factor Model (Fama & French, 1993) extends CAPM by adding size and value factors. It accounts for the tendency of small-cap and high book-to-market stocks to outperform the market. However, despite its improvements over CAPM, empirical tests have shown that the three-factor model does not fully explain stock return anomalies. This led to further refinements in asset pricing models.

Fama and French enhanced their model by including profitability and investment, leading to the development of the Five-Factor Model (Fama & French, 2015). This model incorporates two additional factors: Robust Minus Weak (RMW), which captures differences in returns between firms with robust and weak profitability, and Conservative Minus Aggressive (CMA), which accounts for differences in returns between firms with conservative (low investment) and aggressive (high investment) investment policies. The CMA factor, particularly, is crucial in explaining stock returns as it reflects firms' investment behaviour. According to the model, firms that invest more aggressively tend to have lower expected returns than firms that invest more conservatively. This aligns with the intuition that high-investment firms often rely on external financing, which can be more costly and lead to lower profitability in the long run.

In this dissertation, the focus is on the CMA strategy rather than the CMA factor itself. While both concepts are grounded in the idea that investment behaviour predicts returns, they differ in construction and purpose. The CMA factor is constructed by taking the difference between the average returns on two value-weighted portfolios formed annually: one containing firms with low asset growth (conservative) and another with high asset growth (aggressive).

By contrast, the CMA strategy implemented in this study follows a more simplified and direct approach. Firms are sorted annually into deciles based on their prior asset growth (from year t–2 to t–1), and a long-short portfolio is constructed using the bottom decile (conservative firms) and the top decile (aggressive firms) (Kenneth R. French). This strategy mimics the economic intuition behind the CMA factor but is not used in regression-based pricing models. Instead, it is used to evaluate the performance and profitability of an investment style that exploits differences in firm-level investment behaviour. Thus, while both the CMA factor and strategy are conceptually aligned, this dissertation focuses on the strategy as a practical implementation rather than on the factor as a theoretical pricing component.

The following section reviews a selection of relevant empirical studies that have investigated the relationship between firm investment behaviour and stock returns.

2.2. Empirical Studies on Investment

Following the development of the CMA by Fama & French (2015), several empirical studies have investigated its explanatory power and attempted to uncover the underlying mechanisms driving its profitability. One of the most influential early contributions comes from Cooper et al. (2008), who found a strong negative relationship between asset growth and subsequent stock returns. Their research shows that firms with high asset growth tend to underperform, reinforcing that aggressive investment is linked to overvaluation or lower future profitability. For the purposes of this dissertation, the work of Cooper et al. introduces a behavioural mechanism—investor overreaction—that could apply at the firm and industry levels. When entire industries undergo fast expansion and generate widespread investor enthusiasm, they may attract high-investment firms that ultimately fail to meet expectations.

Similarly, Titman et al. (2004) investigated the relationship between corporate investment behaviour and future stock returns. Specifically, they examined whether firms that undertake substantial increases in capital expenditures (CapEx) subsequently experience abnormally low stock returns. The authors find a strong negative relationship between the magnitude of recent capital investment and future returns, particularly among firms with greater financial flexibility and those with high free cash flow and low leverage, which are more likely to invest without external constraints. They argue that the market often misinterprets large investment spikes as a positive signal of future growth when, in fact, such behaviour may reflect managerial overconfidence or agency problems, leading to overinvestment in low-return projects. As a result, these firms underperform in the following periods. This study offers compelling evidence that aggressive investment strategies can lead to value destruction and reinforces the notion that firms following more conservative investment policies—by allocating capital more efficiently—tend to earn higher average returns.

Therefore, this dissertation seeks to contribute to the ongoing discourse by applying the industry-momentum framework, originally used by Moskowitz & Grinblatt (1999) to the CMA strategy. In the following section, we explore deeper into their study, outlining the methodology they employed and how it supports the analytical framework used in this dissertation.

2.3. Industry Momentum and Moskowitz & Grinblatt

To investigate the relationship between industry concentration and investment strategy profits, I developed my research upon the work of Moskowitz and Grinblatt (1999) in “Do Industries Explain Momentum?”. Although the original study focuses on momentum rather than investment-based strategies, its methodological approach offers valuable insights for this research.

In their study, the authors examine the extent to which industry-level dynamics rather than firm-specific characteristics drive the profitability of individual stock momentum strategies. Their analysis is conducted over an intermediate horizon (6 to 12 months), as the momentum effect tends to be more persistent over this timeframe. The analysis explores various momentum-profits explanations, such as individual stock momentum, cross-sectional variation in mean returns, traditional factor risk, and market microstructure effects. However, the authors conclude that none of these factors contribute to individual stocks momentum strategies profits as significantly as industry momentum does.

Their findings show that a significant portion of the profits from individual stock momentum strategies can be attributed to the performance of the industries these stocks belong. When industry momentum is considered, the profitability of individual stocks decreases, indicating that returns previously attributed to stock momentum are influenced by industry momentum. This suggests that investors can achieve meaningful returns by investing in industries with strong past performance and short-selling those with weak performance. In fact, industry momentum may not only serve as a separate source of profit but also has the potential to outperform individual stock momentum strategies, especially when industry effects are properly accounted for. The authors conducted various tests to study the industry momentum effect, but for the analysis in this dissertation, only four of them are particularly relevant.

2.3.1. Replication and Extension of Moskowitz & Grinblatt

In my analysis, I replicated and extended the original results of Moskowitz & Grinblatt (1999), covering a broader period from July 1926 to December 2023. Next, I will compare the original values with the findings of my analysis to assess consistency and identify potential insights from the extended timeline. This comparison will support assessing how robust the same tests are when applied to study the impact of industry concentration on the profits of investment strategies.

2.3.1.1. Average Profitability of the Momentum Strategy

The initial step of the analysis involved computing the average profits of momentum strategies using a "winners minus losers" approach. These profits represent the initial returns before controlling for other factors that could impact the profitability of momentum strategies. Analysing them works as a benchmark measurement, offering a clear view of how profitable momentum strategies could be under ideal conditions. For individual stock momentum, stocks were ranked based on their prior 6-month returns, forming a zero-cost portfolio by buying the top 30% (winners) and short-selling the bottom 30% (losers). These positions were held for the subsequent 6 months. After doing this, both the original study and my replication and extension presented results that indicate that, under ideal conditions, this strategy generates profits that are not due to chance.

2.3.1.2. Industry-Neutral Portfolio

The next phase of the analysis examines how momentum profits are impacted when industry concentration is considered. Three tests were conducted to explore this effect: Industry Neutral, Excess Industry, and High Industries Losers - Low Industries Winners. The "Industry Neutral" test constructs a zero-cost industry-neutral portfolio by aggregating stocks within each industry, neutralising industry effects. This approach ensures that momentum profits are not driven by a single industry but rather reflect genuine individual stock momentum. From this, a portfolio is constructed by sorting stocks within each industry based on their past six months' returns. Then, a value-weighted average return is calculated by taking the top 30% of stocks and subtracting the performance of the bottom 30%, and this portfolio is held for six months.

2.3.1.3. Excess Industry Portfolio

The "Excess Industry" portfolio takes the analysis a step further by categorising stocks within their respective industries and isolating the excess returns relative to the industry benchmark. Stocks are first ranked based on their past six-month returns, adjusted by subtracting their industry average returns over the same period. The portfolio is constructed by comparing the equal-weighted average return of the top 30% of stocks (those with the highest excess returns) against the bottom 30% (those with the lowest excess returns). If the portfolio generates significant profits, it suggests that individual stock performance contributes meaningfully to momentum strategies. Conversely, if the returns are insignificant or negative, it reinforces the idea that industry effects dominate in driving momentum profits.

The results for the “Industry Neutral” and “Excess Industry” portfolios indicate that when industry effects are neutralised, the profitability of momentum strategies decreases significantly. Moreover, none of the values are statistically significant at any conventional significance level (1%, 5%, or 10%). This finding supports the idea that without the influence of industry momentum, the profits of individual momentum strategies are weak and inconsistent, suggesting that much of the observed momentum profits may be motivated by industry effects rather than individual stock momentum.

2.3.1.4. High Industry Losers Minus Low Industry Winners Portfolio

The final portfolio, "High Industry Losers Minus Low Industry Winners," examines if strategically investing in stocks based on their performance within their respective industries can yield positive returns. Specifically, this test analyses whether going long on underperforming stocks from high-performing industries and shorting top-performing stocks from low-performing industries is a profitable strategy.

To implement this strategy, the three best-performing industries over the past six months are first identified. Within these high-performing industries, stocks are ranked based on their past six-month returns, and a portfolio is constructed using the bottom 30% of stocks. Similarly, a portfolio is created with the top 30% of stocks from the three worst-performing industries. The "Low Industry Winners" returns are then subtracted from the "High Industry Losers" portfolio, resulting in a zero-cost portfolio.

This approach is designed to test the source of momentum profits: if industry effects drive momentum profitability, the portfolio should generate significant positive returns. On the other hand, if individual stock performance is the primary driver, the portfolio is expected to yield significant negative returns.

The original study and my replication and extension yielded strong and statistically significant positive returns for this portfolio. This means that momentum profits are heavily influenced by industry performance, regardless of the specific performance of individual stocks.

Considering the overall results of all the tests, Moskowitz & Grinblatt (1999) concluded that some momentum profits observed in individual stocks can be attributed to industry momentum. Their findings suggest that when industry effects are accounted for, the profitability of individual stock momentum strategies reduces significantly, often becoming statistically insignificant. This reinforces the idea that broader industry trends, rather than individual stock performance alone, play a critical role in driving momentum profits, highlighting the importance of industry concentration in explaining the success of momentum-based investment strategies. When replicating and extending these results, I achieved consistent findings with those of the original authors, demonstrating the robustness and reliability of my analysis. Therefore, I will apply the same approach to study whether industry concentration can explain the profits of the investment strategy (CMA).

Chapter 3
Data Description

The data used in this study were obtained from multiple trustworthy sources, including the (Kenneth R. French Data Library), CRSP (Center for Research in Security Prices), and COMPUSTAT. The sample includes all publicly listed companies in the US, as identified by their respective exchange codes (NYSE, AMEX and the Nasdaq Stock Market). The data was accessed through the WRDS (Wharton Research Data Services) platform, ensuring comprehensive coverage and data integrity. The (Kenneth R. French Data Library)played a particularly crucial role in this research by supplying the CMA strategy factor returns and its methodology for portfolio construction. Additionally, it provided supplementary market data, which served as a benchmark for verifying the accuracy of my results and ensuring their robustness.

To assess the statistical significance of the findings, I employed the *t-statistic* as the primary measure of robustness. It quantifies the degree to which the estimated mean return of a portfolio differs from zero in relation to the standard error of the estimate. It is computed as:

$$t = \frac{\bar{X} - \mu}{SE}$$

Where $\bar{X}$ represents the sample mean, μ is the hypothesised population mean, and SE is the standard error of the mean estimate.

A higher absolute value of the *t-stat* suggests a more substantial likelihood that the observed return is statistically different from zero, reducing the probability that the results are due to chance. A conventional threshold for statistical significance is $|t| >$ 1.96, which corresponds to a 5% significance level, though stronger evidence is indicated when $|t| > 2.58$ (1% significance level).

3.1. Descriptive Statistics

This section presents descriptive statistics for the industry, which provide a baseline understanding of industry behaviours that may impact CMA performance.

Boxplots and histograms (**Erro! A origem da referência não foi encontrada.** & **Figure II**) are used to visualise the distribution of returns across industries, helping to identify variability and outliers. The boxplot, in particular, highlights industries with higher volatility or extreme return values, suggesting that industry dynamics could play a significant role in CMA profitability.

Additionally, the correlation table (**Table III**) compares the average profitability of the CMA investment strategy from my data with results from the (Kenneth R. French Data Library). By assessing how closely my data aligns with Kenneth French's published data, this comparison serves as a robustness check for the reliability of my findings. High correlation values between the portfolios suggest that my results are consistent with established benchmarks, reinforcing the credibility of the analysis.

Table I - Industry-Level Summary Statistics (June 1963 - May 2023).

Table I presents key investment and return characteristics across industries based on SIC classification, covering June 1963 to May 2023. It includes the average number of stocks per industry, with the minimum number at any point in time shown in parentheses. The average investment value reflects firms' typical level of capital expenditure in each industry, indicating their relative aggressiveness or conservatism in investment. The average market capitalisation percentage represents the proportion of total market capitalisation held by firms in each industry, highlighting their relative size in the market. The average monthly return provides an overview of industry-wide performance over time. Additionally, the table includes excess returns, calculated as the difference between the average industry return and the US 3-month Treasury Bill rate. This risk-free rate, used for benchmarking returns, was obtained from United States Rates & Bonds—Bloomberg on March 10, 2025, following the methodology employed in Moskowitz & Grinblatt (1999).

The final row of the table reports the cross-sectional averages of each variable across industries, including the average total number of stocks, average investment value, average market capitalisation share, average monthly return, and average excess return.

Industry	SIC Code	Avg. No. Stocks	Avg. Investment Value	Avg. % of Market Cap.	Avg. % of Monthly Return	Excess Return
Mining	10-14	212,92 (106)	1,76	3,11%	0,95%	0,0059
Food	20	104,02 (53)	0,13	3,43%	1,13%	0,0077
Apparel	22-23	82,01 (18)	0,12	0,33%	0,86%	0,0050
Paper	26	42,0 (15)	0,13	0,74%	1,23%	0,0087
Chemical	28	259,14 (121)	0,30	10,54%	1,33%	0,0097
Petroleum	29	27,55 (10)	0,13	3,23%	1,38%	0,0102
Construction	32	38,37 (9)	0,12	0,25%	1,16%	0,0080
Prim. Metals	33	68,37 (26)	0,36	0,64%	1,13%	0,0078
Fab. Metals	34	90,08 (36)	0,12	0,64%	1,34%	0,0098
Machinery	35	251,82 (110)	0,20	7,34%	1,24%	0,0088
Electrical Eq.	36	319,55 (154)	0,26	6,03%	1,34%	0,0099
Transport Eq.	37	93,42 (57)	0,13	2,72%	1,10%	0,0075
Manufacturing	38-39	261,64 (68)	0,22	3,96%	1,26%	0,0091
Railroads	40	13,80 (2)	0,13	0,64%	1,44%	0,0108
Other Transport.	41-47	83,62 (48)	0,26	1,27%	1,01%	0,0065
Utilities	49	160,13 (80)	0,13	4,22%	1,01%	0,0066
Department Stores	53	41,08 (12)	0,12	2,39%	1,07%	0,0072
Retail	50-52, 54-59	403,60 (138)	0,28	6,18%	1,06%	0,0070
Financial	60-69	788,35 (112)	0,59	15,89%	1,10%	0,0074
Other	other	1187,97 (209)	2,96	26,44%	1,08%	0,0072
Average		**226,47 (69,2)**	**0,42**	**5,0%**	**1,16%**	**0,0080**

Source: Own Elaboration.

Table II - Descriptive Statistics of Industry Returns: Distribution and Volatility Analysis.

Table *II* presents the descriptive statistics of industry returns based on SIC classification from June 1963 to May 2023. The mean indicates the average return for each industry, while the median provides a more robust central tendency measure that is less affected by outliers. The standard deviation captures return volatility. Skewness measures the asymmetry of return distributions, with positive values indicating more frequent significant gains and negative values suggesting frequent large losses. Kurtosis assesses the presence of extreme values, where high kurtosis indicates more significant return spikes and low kurtosis implies a more evenly distributed return pattern.

The mean and median values indicate that most industries exhibit relatively low average returns over time, with several industries showing a median of zero, suggesting that returns often remain stable over multiple periods and are close to zero. The standard deviation, which measures return volatility, reveals that industries such as manufacturing (0,2060), primary metals (0,1678), and machinery (0,1862) experience higher variability, reflecting the cyclical nature of these sectors. In contrast, industries such as railroads (0,1149) and department stores (0,1247) display lower volatility, indicating more stable returns.

The predominantly positive skewness across industries suggests that returns tend to be characterised by occasional extreme positive values, meaning there are periods of exceptionally high returns. The primary metals industry exhibits a skewness of 31,08, while the manufacturing sector records a skewness of 13,65, indicating extreme asymmetry. This suggests that these industries experience occasional large price waves. High kurtosis further reinforces this pattern, implying a greater likelihood of extreme market events. The primary metals sector, with a kurtosis of 3355.29, and the manufacturing sector, with 1146.36, exemplify industries prone to substantial return fluctuations, highlighting their higher risk exposure to extreme market movements.

Industry	**SIC Code**	**Mean**	**Median**	**Standard Deviation**	**Skewness**	**Kurtosis**
Mining	10-14	0,00948	0,0	0,2142	8,30	385,18
Food	20	0,01128	0,0	0,1334	2,60	37,76
Apparel	22-23	0,00858	0,0	0,1587	2,54	40,69
Paper	26	0,01227	0,0031	0,1322	4,18	96,36
Chemical	28	0,01326	0,0	0,2040	5,16	158,51
Petroleum	29	0,01379	0,0059	0,1272	2,13	26,89
Construction	32	0,01157	0,0	0,1413	2,72	40,54
Prim. Metals	33	0,01135	0,0	0,1678	31,08	3355,29
Fab. Metals	34	0,01340	0,0	0,1527	4,22	89,82
Machinery	35	0,01238	0,0	0,1862	3,75	66,25
Electrical Eq.	36	0,01344	0,0	0,2096	6,94	331,85
Transport Eq.	37	0,01103	0,0	0,1530	2,21	29,85
Manufacturing	38-39	0,01264	0,0	0,2060	13,65	1146,36
Railroads	40	0,01441	0,0053	0,1149	4,87	111,86
Other Transport.	41-47	0,01005	0,0	0,1636	3,12	57,06
Utilities	49	0,01015	0,0073	0,1001	4,87	144,76
Department Stores	53	0,01072	0,0	0,1427	2,23	31,41
Retail	50-52, 54-59	0,01056	0,0	0,1858	7,22	330,12
Financial	60-69	0,01099	0,0031	0,1325	3,65	80,12
Other	other	0,01075	0,0	0,2158	7,15	281,75

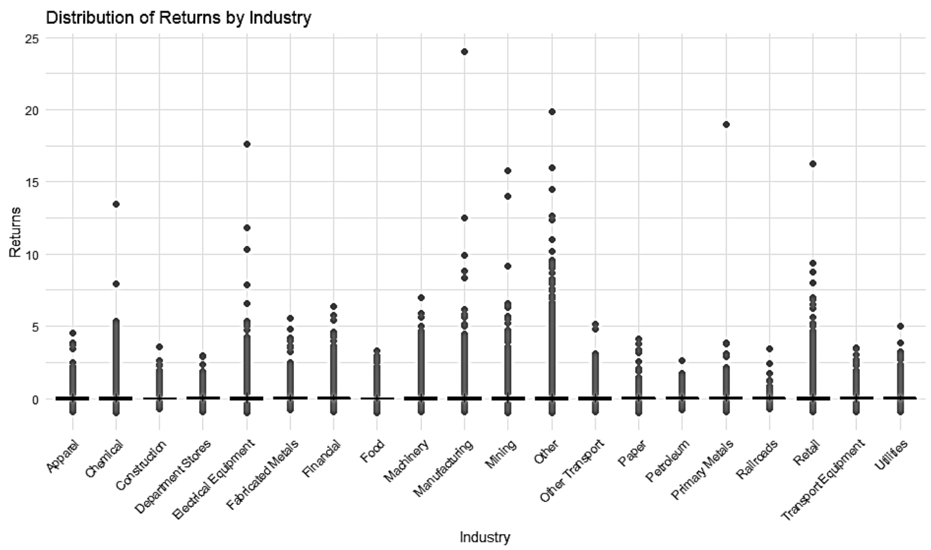
Source: Own Elaboration.

Overall, the data analysis suggests that certain industries, such as petroleum, utilities, and railroads, have more predictable returns with lower volatility. In contrast, sectors like manufacturing, primary metals, and electrical equipment are marked by more unstable returns and a higher propensity for extreme events. These findings underscore the importance of considering industry effects in asset pricing, particularly when analysing investment strategies like CMA, as sectoral variability can significantly impact the profitability of such factors.

The following graphs visually confirm the analysis explained above. The boxplot highlights industry-specific return distributions, showing industries with higher volatility and extreme return events. Meanwhile, the histogram provides insight into the overall return distribution, reinforcing that returns are not symmetrically distributed and exhibit positive skewness, as previously observed in the descriptive statistics. These visualisations further support the findings regarding industry-wide return characteristics and help identify potential anomalies in the data.

Figure I - Distribution of Returns by Industry.

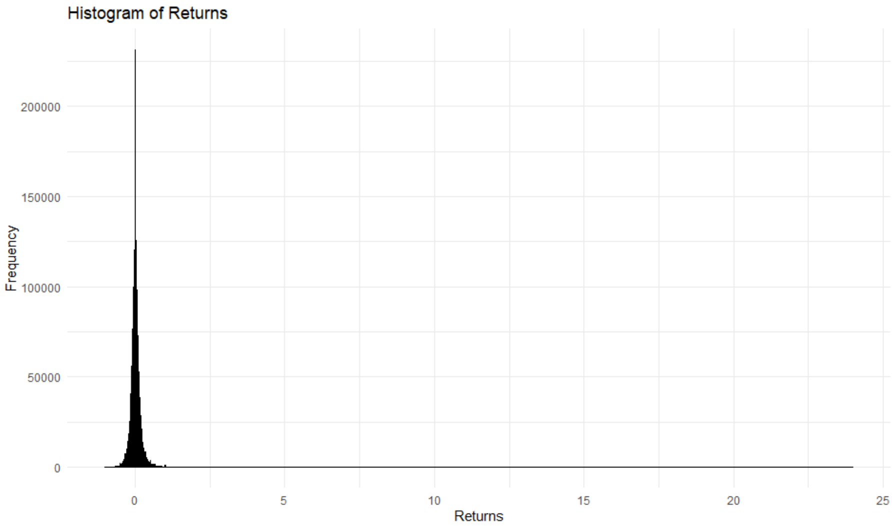
This boxplot displays the distribution of returns across different industries. The central black line represents the median return, while the box captures the interquartile range. The outliers, shown as dots beyond the whiskers, highlight industries with extreme return observations, such as Mining and Other Transport.



Source: Own Elaboration.

Figure II - Histogram of Returns.

This histogram illustrates the frequency distribution of returns across all industries. The strong peak near zero suggests that most returns are clustered around low values, while the long right tail indicates the presence of some highly positive returns.



Source: Own Elaboration.

Table III - Validating CMA Strategy Profitability: A Correlation Analysis with Kenneth French Data.

Table III presents the correlation coefficients of different investment portfolios (Bottom 10%, Top 10%, Bottom 30%, and Top 30%) before controlling for industry effects. The correlations are computed using monthly returns from July 1963 to May 2023 and are compared with the equivalent data retrieved from Kenneth R. French's website (Portfolios Formed on Investment). High correlation values indicate a strong alignment between the constructed portfolios and the original factor returns, reinforcing the dataset's robustness.

	Correlations
Bottom 10%	0,964871853
Top 10 %	0,978486683
Bottom 30%	0,981039329
Top 30%	0,988387496

Source: & Own Elaboration.

3.2. Data Preparation

Let us begin by describing the part common to all four tests: the database preparation. The analysis starts with importing datasets containing stock return information and processing them to ensure reliability. This includes filtering out stocks with missing or zero returns and restricting the sample to ordinary common stocks, which are not further defined and do not require additional specifications. Additionally, only stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the Nasdaq Stock Market (NASDAQ) were included. The dataset also contained specific values representing missing return codes: -66.0, -77.0, -88.0, -99.0 (**Table IV**). These values were removed from the analysis to ensure data integrity. The timeframe chosen for this analysis varies depending on the specific aspect being studied. For the replication of Moskowitz & Grinblatt (1999) results, the period covers July 1963 to July 1995. The extended study, which expands the dataset beyond the original research, covers the period from July 1926 to July 2023. For the analysis of the investment strategy (CMA), the timeframe used was June 1963 to May 2023, aligning with the dataset provided by Kenneth R. French but adapting to the available data, as information for 2024 was not yet accessible at the time of this research.

Table IV - Variables Description.

Detailed description of the variables used during the analysis.

Variable	Description
PERMCO	A unique permanent identifier assigned by CRSP to all companies with securities listed in their database. This identifier remains constant across different securities issued by the company, even in name changes or restructuring cases. PERMCO was the primary firm identifier used in the analysis, with each PERMCO always having an associated PERMNO to track individual securities issued by the same company over time.

PERMNO	A five-digit unique identifier assigned by CRSP to each security. PERMNO does not change throughout a security's trading history and is never reassigned, allowing for consistent tracking of the same security over time.
Share Code	A two-digit code that classifies the type of shares being traded. The first digit describes the type of security (e.g., common stock, preferred stock), while the second digit provides additional classification details.
Exchange Code	Indicates the stock exchange where the security is traded. The primary codes are 1 (NYSE), 2 (AMEX), and 3 (Nasdaq).
Standard Industrial Classification Code (SIC)	A four-digit SIC code is used to classify companies by their primary business activity. The first two digits identify the major industry group, the first three specify an industry group, and all four digits define the specific industry. In this analysis, only the first two digits of the SIC code were considered to classify firms into broad industry groups.
Missing Return Codes	These codes indicate specific reasons for missing returns in CRSP datasets: **-66.0** More than 10 periods between time t and the time of the preceding price t? **-77.0** Not trading on the current exchange at time t **-88.0** No return, array index t not within range of BEGRET and ENDRET **-99.0** Missing return due to missing price at time t
Return (RET)	The monthly return of a security. Negative values indicate a loss; missing values can result from delisting, non-trading periods, or data unavailability.
Investment (INV)	The percentage change in a firm's total assets from year t-2 to year t-1, divided by total assets in t-2.
Date	The observation date is in YYYY-MM-DD format.
Fiscal Year (FYEAR)	In this analysis, the fiscal year corresponds to t-1, meaning that the investment variable is assigned based on the fiscal year ending in t-1 and used for portfolio formation at the end of June in year t.

Source: Center for Research in Security Prices (2025)

Having established the foundational statistics and aligned the data with established benchmarks, the next step is to conduct a detailed empirical analysis. Chapter 4 will present the methodology for replicating and extending the momentum strategy and investigate the influence of industry concentration on the profitability of the CMA strategy.

Chapter 4
Empirical Analysis

This section details the methodology used to replicate and extend the empirical tests originally conducted by Moskowitz & Grinblatt (1999), with a focus on studying the role of industry concentration in explaining the profitability of investment strategies.

First, the analysis begins with replicating the momentum strategy and extending it to a broader time period. This step validates the original study's findings, ensuring the results are robust and reliable.

Once the momentum strategy is validated through this replication and extension exercise, the same methodology is applied to examine the impact of industry concentration on the profitability of investment strategies, specifically the CMA strategy.

Finally, the results are analysed to assess whether industry effects significantly contribute to the profitability of the investment strategies.

4.1. Momentum Strategy Analysis – Results Replication and Extension

In this section, we first outline how the momentum strategy is constructed. The strategy is based on ranking stocks by their past performance and forming portfolios that go long on top-performing stocks and short on bottom-performing ones. After describing the data preparation steps common to all tests (as detailed in Section 3.2.), we will explain the steps that differ across the three tests. Each test will be discussed individually.

4.1.1. Average Profitability of the Momentum Strategy

First, we compute the average profitability of the momentum (APM) strategy to establish a benchmark against which the results of the three subsequent tests will be evaluated. To do this, stocks are ranked based on their past six-month cumulative returns. They are then assigned to ten deciles, with the lowest deciles containing the worst-performing stocks and the highest deciles containing the best-performing ones. The momentum strategy follows a zero-cost portfolio approach, where stocks in the top 30% of performance (deciles 8, 9, and 10) form the long leg, and stocks in the bottom 30% (deciles 1, 2, and 3) form the short leg.

The momentum portfolio is rebalanced every six months to simulate real-world investment strategies. To achieve this, the methodology follows the approach of Jegadeesh & Titman (1993) to address the issue of overlapping returns in momentum strategies. Specifically, for a six-month formation and holding period strategy (6,6), the monthly returns are constructed as an equally weighted average of six independent sub-strategies initiated in different months. For example, the return for January 1992 is calculated as an average of six strategies: one formed in July 1991 and held until December 1991, another formed in June 1991 and held until November 1991, and so on, with each sub-strategy contributing one-sixth of the total return. This approach ensures that no single month's return is overly dependent on a single formation period, thereby reducing autocorrelation in the time series of returns and improving the reliability of statistical tests.

The portfolio return is computed as the stocks' equally weighted average return within each leg. The final momentum return is derived by subtracting the short leg's return from the long leg's return. Once monthly momentum returns are computed, the strategy's average profit is obtained by calculating the mean return across all periods in the sample.

Panel A of **Table V** shows the average profitability for the momentum strategy, comparing the original, replication, and extension results. The original study reports a mean return of 0,43% per month, statistically significant at the 1% level. The replication results yield a slightly lower mean return of 0,38% per month, significant at the 5% level, confirming that the strategy remains effective. When extending the sample period, the mean return decreases further to 0,30% per month, still statistically significant, though profitability has slightly diminished over time.

The replication exercise was successful, as the results closely matched the original study and maintained statistical significance. While the profitability of the momentum strategy slightly decreased in the extended period, it remains positive and significant, indicating that the momentum effect persists, though its impact has reduced over time.

4.1.2. Industry Neutral Portfolio

The industry-neutral test splits stocks by their respective industries before computing past six-month cumulative returns. This approach extends the analysis of individual stock momentum by incorporating industry effects. To achieve this, firms are classified into industries based on their SIC Code. The first two digits of the SIC Code are extracted to define industry groupings (see **Table *I***).

A value-weighted approach is applied, where stock returns are weighted based on market capitalisation, ensuring that larger firms contribute more to the overall portfolio return. To maintain consistency and accuracy in the analysis, firms with missing or zero values for shares outstanding were excluded as their inclusion would distort the weighting process.

After industry classification, firms are ranked within their respective industries based on their past six-month cumulative returns. They are then assigned to deciles, with stocks in the top 30% categorised as winners and those in the bottom 30% as losers. Similarly to the APM strategy, the portfolios are rebalanced every six months using the overlapping return methodology to mitigate autocorrelation effects. The returns of selected stocks in the Top 30% and Bottom 30% portfolios are recorded over the next six months. Stocks from different industries are aggregated to create a comprehensive industry-neutral portfolio. A zero-cost portfolio is formed by taking a long position in the Top 30% of stocks and a short position in the Bottom 30%. Portfolio returns are then computed as the difference between the long and short legs, and the final return is obtained as the value-weighted average across six independent formation periods. Finally, once individual monthly industry momentum returns are computed, the mean return of the strategy is derived by averaging across all sample periods.

The original results report a mean return of 0,0011 per month, with a t-statistic of 1,11, which is not statistically significant at conventional levels. The replication results show a mean return of 0,0023 per month, with a t-statistic of 1,53, which is also not statistically significant at the 1% or 5% levels. Finally, the extension results yield a mean return of 0,0011 per month, with a t-statistic of 0,95, which is also statistically insignificant (**Table V**—Panel B).

These results indicate that when industry effects are neutralised, the profitability of the momentum strategy decreases significantly. Furthermore, none of the values are statistically significant at conventional significance levels (1%, 5%, or 10%). This finding supports the idea that without the influence of industry momentum, the profits of individual momentum strategies are weak and inconsistent, suggesting that much of the observed momentum profits may be driven by industry effects rather than individual stock momentum.

4.1.3. Excess Industry Portfolio

This test closely resembles the industry-neutral test but takes the analysis a step further by isolating excess returns relative to the industry benchmark.

Similarly to the previous test, firms are classified into industries based on their SIC Code. To compute industry-adjusted returns, each industry's average return is calculated every month. Each stock's return is then adjusted by subtracting the mean return of its industry, yielding an industry-neutral return. This adjustment ensures that any momentum effect observed in the strategy is not simply a reflection of industry performance but individual stock effects. This test also modifies the past six-month cumulative returns calculation by applying a two-step industry adjustment process. Instead of directly compounding the industry-adjusted returns, the six-month cumulative returns are first computed using non-adjusted returns. Then, the average six-month return is calculated for each industry. Finally, the industry average is subtracted from the non-adjusted six-month return of each stock. This approach ensures that the cumulative returns entirely isolate excess returns relative to the industry, providing a clearer measure of stock-specific momentum. After that, firms are ranked into deciles based on their industry-adjusted past six-month returns, with the top 30% classified as winners and the bottom 30% as losers. Unlike the previous test, this approach does not apply value weighting. From this point onward, the methodology follows the same approach as the previous momentum tests.

In Panel C (**Table V**), the original results show a mean return of -0,0007 per month, with a t-statistic of -0,83, which is not statistically significant. The replication results show a slight positive mean return of 0,0003 per month, with a t-statistic of 0,27, which is also not statistically significant. Finally, the extension results show a mean return of 0,0019 per month, with a t-statistic of 1,66, also not statistically significant at the conventional 5% level.

These results indicate that the strategy's profitability is weak when adjusting for industry effects. While the replication and extension results show positive returns, they are not statistically significant at the conventional level. This suggests that isolating excess returns relative to industry benchmarks does not lead to a strong, consistent momentum effect. Therefore, much of the observed profitability in momentum strategies could be attributed to broader industry effects rather than stock-specific momentum.

4.1.4. High Industry Loser Minus Low Industry Winners Portfolio

This test differs from the previous methodologies by examining whether industry momentum alone can generate significant profits instead of assessing momentum at the individual stock level. The strategy involves investing in losing stocks from high-performing industries and shorting winning stocks from low-performing industries, thereby isolating the influence of industry momentum in explaining returns.

To do that, after preparing the data, the firms are also classified into industries using their SIC code. Then, the best and worst-performing industries each month were identified. To achieve this, industry-level returns are calculated as the average past six-month return of all firms within each industry for a given month. At the end of each month, industries are ranked based on this, and the top three industries (with the highest average six-month return) and bottom three industries (with the lowest average six-month return) are selected.

Once the top three and bottom three industries are identified, the strategy then selects individual stocks within these industries. Within the top three industries, the worst-performing stocks (bottom 30% based on six-month past returns) are selected, while within the bottom three industries, the best-performing stocks (top 30% based on six-month past returns) are chosen. This approach ensures that the portfolio captures the momentum effect at the industry level rather than relying solely on individual stock performance.

After selecting stocks, a long position is taken in the losing stocks from the best-performing industries, and a short position is taken in the winning stocks from the worst-performing industries. Stocks are equally weighted within each leg, ensuring that no single firm disproportionately influences the results. The portfolio is rebalanced every six months to mitigate autocorrelation effects. Similarly to the previous portfolios, the portfolio is rebalanced every six months to mitigate autocorrelation, with the final return calculated as the difference between the long leg (losing stocks in high-investment industries) and the short leg (winning stocks in low-investment industries). This isolates the effect of industry momentum. The results help assess whether industry trends alone can drive significant investment profits.

Panel D of **Table V** shows the High Industry Losers Minus Low Industry Winners strategy results. The original results show a mean return of 0,30% per month, with a t-statistic of 2,66, which is statistically significant at the 5% level. The replication results yield a mean return of 0,89% per month, with a t-statistic of 5,77, which is statistically significant at the 1% level. Finally, the extension results show a mean return of 0,63% per month, with a t-statistic of 5,6, which is also statistically significant at the 1% level.

This shows that industry momentum can indeed generate significant profits. All three sets of results (original, replication, and extension) show statistically significant positive returns. This suggests that industry-level momentum plays a crucial role in driving profitability, confirming that broader industry trends, rather than individual stock momentum alone, significantly contribute to the success of this strategy.

Table V - Momentum Strategy Profits: Moskowitz & Grinbaltt Results, Replication, and Extended Results.

Panel A presents the average profitability of the momentum strategy, with the original results from Moskowitz & Grinblatt from 1963 to 1995, replication results for the same period, and extension results for 1926-2023, highlighting the strategy's performance across different periods.
Panel B shows the results for the Industry Neutral Portfolio, comparing the original, replication, and extension results. This test adjusts stock returns for industry performance, isolating the impact of momentum strategy profitability when controlling for industry effects.
Panel C presents the Excess Industry Portfolio, focusing on the original, replication, and extension results. It isolates excess returns relative to the industry benchmark to better understand the stock-specific momentum profits.
Panel D displays the High Industry Losers Minus Low Industry Winners Portfolio, showing the original, replication, and extension results. This test focuses on whether industry momentum alone,

rather than individual stock momentum, can generate significant profits by investing in losing stocks from high-performing industries and shorting winning stocks from low-performing industries.

Panel A: Average Profitability of the Momentum Strategy					
Original Results		Replication Results		Extension Results	
Mean	(*t-stat*)	Mean	(*t-stat*)	Mean	(*t-stat*)
0,0043	(4,65**)	0,0038	(2,14*)	0,0030	(2,30**)
Panel B: Industry Neutral Portfolio					
Original Results		Replication Results		Extension Results	
Mean	(*t-stat*)	Mean	(*t-stat*)	Mean	(*t-stat*)
0,0011	(1,11)	0,0023	(1,53)	0,0011	(0,95)
Panel C: Excess Industry Portfolio					
Original Results		Replication Results		Extension Results	
Mean	(*t-stat*)	Mean	(*t-stat*)	Mean	(*t-stat*)
-0,0007	(-0,83)	0,0003	(0,27)	0,0019	(1,66)
Panel D: High Ind, Losers – Low Ind, Winners Portfolio					
Original Results		Replication Results		Extension Results	
Mean	(*t-stat*)	Mean	(*t-stat*)	Mean	(*t-stat*)
0,0030	(2,66**)	0,0089	(5,77**)	0,0063	(5,96**)

*, ** Significant at 5 and 1 percent levels, respectively,

Source: Moskowitz & Grinblatt (1999) for the Original Results & Replication and Extension Results by the author of this dissertation.

4.2. Investment Strategy Analysis

To conduct the investment strategy analysis, we utilise Kenneth French's investment-based portfolios. These portfolios are formed based on the percentage change in total assets from the fiscal year ending in t-2 to t-1, divided by total assets in t-2. The classification is updated annually at the end of June using NYSE breakpoints.

Following this approach, we adapt it to the methodology Moskowitz & Grinblatt (1999) employed in their study of momentum strategies, as previously detailed in section 4.1. This allows us to integrate industry dynamics into the analysis. This time, an additional 10% breakpoint strategy was introduced alongside the previously implemented 30% breakpoint strategy to enable a more detailed analysis.

The process begins with data preparation, where stock return data sets are imported and cleaned to ensure accuracy. Stocks with missing or zero returns are removed, and the dataset is restricted to common stocks listed on the NYSE, AMEX, and Nasdaq exchanges. Initially, only NYSE-listed firms are considered for breakpoint computation each June. This filtering is applied temporarily but then removed to include all relevant stocks in the analysis. Additionally, portfolios formed in June are based on investment values from t-1, which reflect the percentage change in total assets from t-2 to t-1. This transformation aligns with Kenneth French's investment strategy, which assigns the investment variable from year t-1 to June of year t.

After computing the breakpoints, firms below the $30^{th}/10^{th}$ percentile are categorised as low investment, while those above the $70^{th}/90^{th}$ percentile are classified as high investment. Based on these classifications, stocks in the bottom 30% (or 10%) investment category are identified in June each year and tracked for the following 12 months, as are stocks in the top 30% (or 10%) category.

Unlike some prior tests that employ equal weighting, this analysis always uses a value-weighted approach, meaning each firm's contribution to the portfolio return is weighted by its market capitalisation. The market cap is calculated as the product of stock price and shares outstanding. In June of each year, the total market capitalisation of each investment category is computed, and individual stock weights are determined as the firm's market cap divided by the total market cap of its investment group. These weights remain fixed over the subsequent 12 months, ensuring portfolio returns accurately reflect firm size.

The final portfolio return is calculated as the sum of the individual firm returns weighted by market capitalisation.

After obtaining the value-weighted portfolio returns, the CMA strategy is computed as the difference in returns between firms with low and high investment value. Two versions of this strategy are analysed: one based on the 30%- 70% breakpoints and another based on the 10%- 90% breakpoints. Monthly returns for both strategies are computed from June 1963 to May 2023, and the annual average return of each strategy is obtained.

As presented in **Table *VI*** – Panel A, the monthly returns without industry adjustments are positive and significant for the 10% and 30% strategies (means: 0,0042 and 0,0019; *t-stat*: 3,32 and 2,11, respectively). This suggests that the CMA strategy captures a persistent return premium, indicating that low-investment firms are rewarded with higher stock returns than high-investment firms.

Let us examine whether the interpretation holds when accounting for industry effects. To proceed, I will focus on the top 10%—bottom 10% strategy, as it yields higher returns and provides a stronger signal for analysis. However, for the sake of robustness, we will also demonstrate the results for the top 30% - bottom 30% strategy in **Table VI** – Panel B. While this strategy generates slightly lower returns, it provides additional insight into the influence of industry effects across different percentiles, enriching our understanding of the relationship between industry concentration and CMA profitability.

4.2.1. Industry Neutral Portfolio

On Industry Neutral Portfolio, firms are categorised into industries based on their SIC codes. Then, investment percentiles (top 10% and bottom 10%) are calculated separately for each industry rather than across the entire market.

The portfolio formation process remains consistent with the previous methodology. Each June, stocks in the bottom 10% and top 10% investment categories are selected based on their industry-specific breakpoints. These firms are then tracked over the following 12 months, and their monthly returns are aggregated to calculate portfolio returns.

A value-weighted approach is also applied, where firm weights are assigned based on market capitalisation and fixed for the entire holding period. However, since industry categorisation is considered, the market cap calculation occurs within each industry segment, ensuring that the weighting is not biased by disproportionately large or small industries.

By constructing these industry-adjusted portfolios, this test provides a more refined analysis of whether the CMA strategy remains significant after controlling for industry effects. If the return spread between low- and high-investment firms persists, it suggests that investment profitability is driven by firm-level decisions rather than industry-wide trends.

The result presented in **Table VI**—Panel A shows that the strategy continues to generate positive returns even after controlling for industry influence. The strategy yielded a positive and significant mean profit of 0,0029, which, compared to the average profitability investment strategy (which yielded a 0,0042 mean return), this industry-neutral version produces a slightly lower return. This suggests that industry effects influenced part of the average profitability of the investment strategy, but firm-specific investment decisions still contribute significantly.

4.2.2. Excess Industry Portfolio

For the Excess Industry test, the approach remains consistent with previous methodologies but introduces an additional adjustment. Here, investment values are industry-adjusted by subtracting the industry's mean for each year, ensuring that investment classifications are independent of industry-wide trends.

Following this, firms are ranked based on their adjusted investment levels, and breakpoints (10^{th} and 90^{th} percentiles) are computed within each industry-year group. The portfolio formation process remains unchanged—stocks are assigned to their respective investment categories each June, and returns are tracked over the following 12 months using a value-weighted methodology.

The top-bottom 10% Excess Industry strategy produces a monthly mean return of 0,33% with a *t-stat* of 2,88, indicating statistical significance at the 1% level. This suggests that even after controlling for industry effects, firms with the lowest investment levels continue outperforming those with the highest investment. Compared to the Industry Neutral test (0,029 vs. 0,033), the return increase implies that industry effects might have partially reduced investment strategy returns. However, the strategy remains profitable even after removing industry-wide trends. This further strengthens the argument that the investment strategy is driven by firm-specific investment behaviour rather than broader industry-level influences.

Finally, we move on to the final test: High Industry Losers – Low Industry Winners. If this test yields a negative mean return or a statistically insignificant result, it suggests that the investment strategy is not significantly influenced by industry concentration, reinforcing that industry trends may not be the primary driver of returns.

4.2.3. High Industry Losers Minus Low Industry Winners Portfolio

This final test compares firms in the worst-performing industries regarding investment levels with those in the best-performing industries. Instead of neutralising industry effects or adjusting investment levels relative to industry averages, this test takes a more specific approach. Industries are ranked annually by their average investment levels, with the top three classified as high-investment industries and the bottom three as low-investment industries. Two portfolios are formed: high-industry losers, which consists of firms in high-investment industries but in the bottom 10% for investment, and low-industry winners, which includes firms in low-investment industries but in the top 10% for investment. By comparing the performance of these portfolios, this test evaluates whether firms' investment-driven returns are influenced by the broader investment behaviour of their respective industries. After forming the portfolios, returns are calculated using value-weighting, ensuring that larger firms exert a proportionate influence on the final portfolio return. The test measures the return difference between these two portfolios to determine whether industry investment dynamics significantly impact the profitability of the CMA strategy.

Panel A of **Table VI** shows that the return difference between high-industry losers and low-industry winners is 0,22% per month, with a *t-statistic* of 1,12. This value suggests a lack of strong statistical significance, as the *t-statistic* is below the conventional threshold of 1,96 for 5% significance. The positive mean return implies that firms classified as losers in high-investment industries do not significantly underperform relative to winners in low-investment industries. However, the low *t-statistic* means that this result is not robust enough to conclude that industry effects systematically drive the observed returns. This reinforces the notion that industry concentration does not meaningfully explain the profitability of the investment strategy. Instead, it suggests that firm-level investment decisions remain the dominant driver of returns in the CM2A strategy, independent of industry-wide investment behaviour.

Table VI - Monthly Investment Strategy Returns by Type of Portfolio.

Table **VI** presents the monthly investment strategy returns by type of portfolio, summarising the mean returns and statistical significance for different portfolio construction approaches. It provides a structured comparison of various investment strategies used in this study, highlighting how returns change depending on how industry effects are accounted for.

Panel A focuses on the top 10%/bottom 10% strategy, while Panel B refers to the top 30%/bottom 30% strategy. In the Average Profitability of the CMA Strategy, bolded values represent the results retrieved from Kenneth French’s website for comparison and robustness checks.

Panel A: Monthly Investment Strategy Returns by Type of Portfolio – (Bottom 10% & Top 10%)		
	Mean	(*t-stat*)
Average Profitability of CMA Strategy	0,0042 – **(0,0040)**	(3,32**) – **(3,15**)**
Industry Neutral	0,0029	(2,60**)
Excess Industry	0,0033	(2,88**)
High Ind. Losers – Low Ind. Winners	0,0022	(1,12)
Panel B: Monthly Investment Strategy Returns by Type of Portfolio – (Bottom 30% & Top 30%)		
	Mean	(*t-stat*)
Average Profitability of CMA Strategy	0,0019 – **(0,0021)**	(2,11**) – **(2,15**)**
Industry Neutral	0,0020	(2,50**)
Excess Industry	0,0019	(2,54**)
High Ind. Losers – Low Ind. Winners	0,0025	(1,57)

*, ** Significant at 5 and 1 percent levels, respectively.

Source: Own Elaboration.

After conducting the analysis with the Industry Neutral Portfolio, Excess Industry Portfolio, and High Industry Losers Minus Low Industry Winners Portfolio, the results indicate that industry concentration does not significantly drive CMA profits. While the Average Profitability of the CMA Strategy remains positive even after adjusting for industry effects, the profitability decreases slightly, and the results are not as significant when accounting for industry dynamics. Specifically, while the Industry Neutral and Excess Industry tests show some level of profitability, the High Industry Losers Minus Low Industry Winners strategy reveals no significant statistical relationship between industry concentration and CMA profits. These findings suggest that industry concentration plays a minor role in explaining CMA profits, and broader industry trends have less influence on the strategy’s profitability. Compared to momentum strategies, where industry effects are more pronounced, the influence of industry concentration on CMA profits is less significant.

Chapter 5
Conclusion

This dissertation examined whether industry concentration explains the profitability of the Conservative Minus Aggressive (CMA) investment strategy. By replicating and extending the results of Moskowitz & Grinblatt (1999) and adapting their methodology to the CMA strategy analysis, this research aimed to determine whether industry effects play a significant role in driving CMA returns.

5.1. Does Industry Concentration Drive CMA Strategy Profits?

After analysing with three different tests—an Industry Neutral Portfolio, an Excess Industry Portfolio, and a High Industry Losers plus Low Industry Winners Portfolio—we find that industry concentration does not significantly drive CMA profits.

The average profitability of the CMA initially shows positive returns, but once industry effects are accounted for, the profitability decreases. While some adjusted results remain positive, they do not achieve statistical significance in all cases. Specifically:

1. **Industry Neutral Portfolio:** After accounting for industry effects, the CMA strategy still shows positive returns, but the profitability decreases slightly. While the strategy remains significant with a mean return of 0,0029, this result is lower than the Average Profitability of the CMA Strategy (0,0042), indicating that industry effects indeed influenced part of the profitability.
2. **Excess Industry Portfolio**: This test isolates excess returns relative to industry benchmarks and still shows statistically significant positive returns (mean return of 0,0033). This confirms that the CMA strategy remains profitable even after controlling for industry effects.

3. **High Industry Losers Minus Low Industry Winners Portfolio:** The return difference here is 0,22% per month, with a *t-statistic* of 1,12, which is not statistically significant. This result suggests that industry concentration does not systematically explain the profitability of the CMA strategy. The low *t-stat* indicates that industry effects are not robust enough to influence the strategy's returns, reinforcing the notion that firm-level investment decisions dominate in driving the profitability of the CMA strategy.

Given these results, we conclude that industry concentration does not significantly impact the profitability of the CMA strategy. At the same time, industry effects may substantially influence other strategies (such as momentum). This finding suggests that, unlike momentum, the profitability of CMA is more dependent on the firms' individual characteristics and investment decisions rather than on the broader industry forces.

5.2. Limitations and Future Research

Despite the robustness of the analysis, this study faced several limitations. First, the lack of advanced programming knowledge posed challenges in efficiently processing large datasets and implementing complex analytical methods. The analysis required significant computational effort, which could have been optimised with greater expertise in data management and automation techniques. Second, hardware constraints also presented difficulties. The computational resources available were not optimal for running large-scale financial analyses, leading to prolonged processing times. Future research could benefit from improved computational resources and advanced coding techniques to enhance the efficiency and scalability of similar analyses.

Given the findings and limitations of this study, several possibilities for future research emerge. First, this analysis could be extended to other countries and regions to determine whether industry concentration plays a more significant role in different economic and market structures. Second, future studies could examine whether the impact of industry concentration on the CMA strategy changes over time, particularly during financial crises or economic downturns. Another potential avenue would be to explore alternative ways of measuring industry concentration, such as using different thresholds or industry classifications, to see if the results remain consistent. Finally, incorporating other firm-specific factors, such as leverage, liquidity, or size, could provide further insight into what drives the profitability of the investment strategy.

In summary, while this study finds that industry concentration does not significantly influence the CMA strategy's profitability, it opens the door for future research to explore alternative explanations in asset pricing and factor investing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of my written thesis, "Does Industry Concentration Explain the Profitability of the CMA Strategy?", ChatGPT (OpenAI) was used for the following tasks: Clarifying academic language and grammar, Improving the structure and coherence of some paragraphs, Helping with translation from Portuguese to English (and vice versa); Assisting in brainstorming titles and descriptions; Supporting the development and debugging of R code used for data analysis, with the prompts used listed at the end of the document in the Prompts List section. After using this tool, I reviewed and edited the content as necessary, and I take full responsibility for the content of the work presented.

I also declare that I am aware of and respect the Artificial Intelligence Rules of Conduct of Católica Porto Business School.

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Appendices

List of Abbreviations/ Acronyms

AMEX – American Stock Exchange

APM – Average Profitability of the Momentum

APT – Arbitrage Pricing Theory

BEGRET – Beginning of Return Period

CapEx – Capital Expenditure

CAPM – Capital Asset Pricing Model

CMA – Conservative Minus Aggressive

CRSP – Center for Research in Security Prices

ENDRET – End of Return Period

EXCHCD – Exchange Code

FF3F – Fama-French Three-Factor Model

FF5F – Fama-French Five-Factor Model

FYEAR – Fiscal Year

INV – Investment

IQR - Interquartile

MPT – Modern Portfolio Theory

NYSE – New York Stock Exchange

PERMCO – Permanent Company Identifier

PERMNO – Permanent Number Identifier

RET – Returns

RMW – Robust Minus Weak

SHRCD – Share Code

SIC – Standard Industrial Classification

US – United States

WRDS – Wharton Research Data Services

Prompts List

1. *Improve the grammar and clarity of this paragraph.*
2. *Translate this paragraph from Portuguese to English using an academic tone.*
3. *Suggest a better title for this chapter/section.*
4. *Help me structure this paragraph more clearly.*
5. *Correct the academic tone of this statement.*
6. *What is a synonym for "xxx"?*
7. *How can I make this transition between paragraphs smoother?*
8. *Rewrite this sentence to avoid repetition.*
9. *Check if this abstract has a clear structure.*
10. *Summarize this paragraph in 2-3 sentences.*
11. *Review this section title and suggest improvements.*
12. *Help me improve the logical flow of this paragraph.*
13. *How do I cite this study properly in APA?*
14. *How can I improve the efficiency of this R loop?*
15. *This R code is not giving the expected result – what could be wrong?*
16. *My R code gives an NA result — how do I fix this?*
17. *What is a more straightforward way to write this function in R?*
18. *How to read an Excel file on R?*
19. *How can I create a boxplot and histogram on R?*
20. *My code is displaying the following error. What does it mean, and how can I solve it?*