UNIVERSIDADE CATÓLICA PORTUGUESA

Does Industry Concentration Drive the Value Premium?

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by

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Abstract

This study investigates whether industry concentration drives the value premium, reproducing its documented effect on momentum. Replicating and extending the framework of Moskowitz & Grinblatt's (1999), this analysis constructs strategies isolating industry effects for both the momentum and value anomalies for U.S. equities. While an overall decay and industry-components dependence by momentum premia is reported, value premia shows different patterns. Pure value strategies generate non-significant premiums, with Industry Neutral strategies achieving robust 0,37% monthly returns, signalling firm-specific characteristics dependence. Excess-industry and cross-sector contrarian value strategies report non-significant premiums, indicating minimal industry influence. Thus, while momentum profitability is amplified by industry concentration, we do not observe the same effect for value.

Keywords: Momentum, value premium, industry concentration, factor investing, cross-sectional anomalies

Wordcount: 7766

Resumo

Este estudo investiga se a concentração setorial impulsiona o prémio de *value*, reproduzindo o seu efeito documentado no *momentum*. Replicando e expandindo a estrutura de Moskowitz & Grinblatt (1999), a análise constrói estratégias que isolam efeitos setoriais para ambas as anomalias em ações dos EUA. Embora seja observado um declínio geral e uma dependência de componentes setoriais nos prémios de *momentum*, os prémios de *value* exibem padrões distintos. Estratégias puras de *value* geram prémios não significativos, enquanto estratégias neutras em relação ao setor alcançam retornos robustos de 0,37% ao mês, sinalizando dependência de características específicas das empresas. Estratégias de *value* com ajuste setorial (excesso de indústria) e contrárias intersetoriais também relatam prémios não significativos, indicando influência mínima do setor. Desta forma, enquanto a lucratividade do *momentum* depende de tendências setoriais amplificadas pela concentração de mercado, o mesmo efeito não é observado quanto ao *value*.

Keywords: *Momentum*, prémio de *value*, concentração setorial, investimento em fatores, Anomalias transversais

Contagem de palavras: 7766

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Introduction

Understanding the drivers behind the persistence of cross-sectional anomalies[1] is fundamental to asset pricing theory, as factor investing has become a foundation of modern portfolio theory. Among these anomalies, the value premium captured by forming long positions on stocks with high book-to-market (B/M) ratios and short positions on stocks with low B/M ratios and the momentum premium captured by the excess return of stocks with high historical returns over stocks with low historical returns remain two of the most studied anomalies (Fama & French, 2004).

The aim of this thesis lies in addressing the question: "Does industry concentration drive the value premium?". By analysing whether industry concentration drives the profitability behind value-based strategies we are able to observe whether it is rooted in systematic risks, behavioural anomalies or exploitable market inefficiencies, having implications in market efficiency and investment strategies. If industries with low market valuation (high B/M) drive the value premium, this could suggest that profitability arises from shared sector risks, signalling that these investment strategies are not well diversified, since the stocks driving the profitability of the strategy are all in a few industries, thus requiring higher compensation. Alternatively, if the value premium remains robust after controlling for industry effects, it would imply that firm-level undervaluation plays a central role in value profitability.

While momentum's dependence on industry dynamics is well documented, the role of industry concentration in explaining the value premium remains underexplored. Fama & French (1992, 1993) established the value premium,

[1] An anomaly refers to a persistent deviation from the predictions of established asset pricing models such as the Capital Asset Pricing Model, generating abnormal risk-adjusted returns (Lintner, 1965; Sharpe, 1964).

showing that high B/M stocks outperform low B/M stocks, a finding later replicated globally (Fama & French, 1998). Competing explanations on what its drivers are include risk-based theories[2] and behavioral narratives[3]. However, these studies focus on firm-level characteristics or market risks, without focusing on industry structure.

This study contributes to the literature in two ways. First, it replicates Moskowitz & Grinblatt's (1999) momentum analysis for the original sample period (1963-1995) and then extends it to an extended sample (1926–2023), confirming the dependency of the momentum premium on industry concentration as well as reporting its decay, consistent with the extant literature[4]. Second, it adapts their framework to the value factor, constructing portfolios that neutralize or exploit industry effects, not having observed the same industry concentration dependence of the value premium as found in momentum premium.

Along with a pure momentum strategy, Moskowitz & Grinblatt's (1999) methodology isolates industry components through three strategies: Industry Neutral (ranking stocks within each industry), Excess-Industry (ranking stocks by adjusting them by their industry's average factor metric) and cross-industry contrarian strategies (pairing low stocks in high industries against high stocks in low industries according to the factor's metric).

For momentum, 30% breakpoints are used to form the long (highest 30%) and short (lowest 30%) portfolios with momentum returns being defined as the past six months cumulative returns for each stock, having a holding and rebalancing period of six months. Their analysis is replicated for momentum based on their original sample period (1963 until 1995) and extended to a larger sample

[2] Zhang (2005) states that value stocks reflect exposures to financial distress.
[3] Lakonishok et al. (1994) state that value and growth stocks reflect overreactions to past performance.
[4] Daniel & Moskowitz (2016) investigate momentum in the 21st century having found that its premium decayed due to severe market crashes and time-varying exposure to market volatility.

containing data from 1926 until 2023. For value, strategies are defined using NYSE-based 10th and 90th percentile B/M breakpoints, annually rebalancing long positions in high B/M stocks and short positions in low B/M stocks for a sample period from 1970 until 2023. CRSP and Compustat were used as the main data sources to build the strategies.

Pure value strategies resulted in non-significant premiums, generating 0.35% average monthly returns (t-stat = 1.80), aligning closely with benchmarks from Kenneth French's dataset (4.18% vs. 4.26% annualized). Industry Neutral value strategies achieved robust and significant premiums of 0.37% monthly average returns (t-stat = 2.33), outperforming pure value strategies. On the other hand, the Excess Industry (0.21%, t-stat = 1.44) and High Industry Growth minus Low Industry Value (0.32%, t-stat = 1.53) reported non-significant results. Since the only strategy that revealed to be significantly profitable was the one that forcibly buys and sells within all industries (both high B/M and low B/M) regardless of sectoral trends, these results signal that the value premium depends on firm-level characteristics rather than industry concentration, contrary to the findings reported for momentum where industry performance revealed to be central to the strategy.

This paper is organized as follows. Chapter 1 comprehends the literature review going over the theoretical foundations of factor models, the role of industry components in momentum premia and extant literature on the value anomaly. Chapter 2 details the data sources and describes the datasets used for forming the momentum and value strategies. Chapter 3 provides the rationale for the strategy formation for the momentum and value anomalies. Finally, Chapter 4 summarizes the findings, discussing implications for factor investing in concentrated markets and proposing future research avenues.

1. Literature Review

A fundamental line of research within finance is understanding the drivers of asset returns and, more specifically, analysing variations in the cross-section of stock returns—i.e., differences in returns across individual stocks at a given point in time. Such variations arise from the interactions of the firms which underlie the stocks with the environments in which they operate, be it the macro environment (e.g., economic conditions and market trends) and the microenvironment (e.g., firm-specific characteristics and industry dynamics).

In order to explain these variations and interactions, academics have developed factor models that continue to have widespread applications across the financial markets for portfolio management, risk management, cost of capital estimations, among others, serving as the focus of this thesis as well.

1.1 Cross-section of Returns and Factor Models

The analysis of differences in stock returns at a given point in time seeks to identify cross-sectional signals, referring to systematic factors that explain why certain stocks outperform others within the same period. This approach isolates characteristics such as value (high book-to-market ratios) or momentum that drive return disparities across assets (Fama & French, 1993). Cross-sectional analysis differs from time series analysis, which examines how returns for a single asset evolve over time, focusing on temporal patterns like volatility clustering or mean reversion. The two methodologies are complementary: cross-sectional tests identify predictive factors, while time series regressions, as employed by , validate whether those factors capture shared risk exposures across portfolios over time (Fama & French, 2004).

Having been based on the work of Markowitz (1952), the Capital Asset Pricing Model (CAPM), a model that focuses on the cross-section of returns, established a new understanding of the connection between expected return and systematic risk. In this model, it is stated that the market portfolio is the optimal risky portfolio, being mean-variance efficient—i.e., offering the best risk-return trade-off deemed theoretically possible across the universe of all investable stocks (Lintner, 1965; Sharpe, 1964).

Among the core assumptions of the model is the belief that investors achieve perfect diversification, completely eliminating all oosyncratic risk, leaving systematic risk as the sole determinant of differences in expected returns. This hypothesis sets the idea that the market βs, the linear coefficients that capture systematic risk and attempt to explain the relationship of a security's variance of returns with that of the market portfolio, are sufficient to explain the variability in the cross-section of returns. On the other hand, over time several empirically observed shortcomings of CAPM's market factor were raised, and patterns or behaviours on asset returns that couldn't be explained by the model, named anomalies, started to become more and more frequent, making the term gain traction (Fama & French, 1992).

(Fama & French, 1993, 1996) establish the first of a series of models, the Fama-French Three Factor model (FF3F), that added the previously mentioned systematic cross-sectional signals to the original market factor. These newly added signals, the size factor (SMB) and the value factor (HML), the focus for this thesis, capture the excess returns associated with smaller firms and value stocks, respectively, that are not captured by the market return and are priced separately from market betas (Fama & French, 2004).

Multiple improvements to the FF3F model were developed. (Carhart, 1997; Jegadeesh & Titman, 1993) incorporate the momentum factor into the FF3F model, recognizing the tendency of stocks that have performed well in the past (winners) to continue performing well in the future, and stocks that have performed poorly (losers) to continue underperforming. Fama & French (2015) introduce the Fama-French Five Factor model (FF5F) incorporating the profitability (RMW) and the investment factor (CMA) into the FF3F model, which capture the tendency of firms with high profitability (robust) to generate higher returns compared to firms with low profitability (weak) and the tendency of firms that invest conservatively to outperform firms that invest aggressively, respectively.

1.2 Industry Effects in Momentum Premia

Examining the effects of industry components on persistent stock return anomalies is of great importance to the understanding of the risk-adjusted returns of said anomalies, allowing the separation of systematic risk exposures from behavioural or structural explanations. Moskowitz & Grinblatt (1999) first isolated and quantified the link between industry and individual momentum premia, having found that momentum investment strategies are significantly less profitable once controlled for industry momentum. With their analysis, the conventional view of momentum as an individual stock-level phenomenon was challenged and the idea that correlated industry exposures drive most of the factor’s profitability was established instead. This finding allows us to better understand the risk profile of the momentum anomaly, leading us to believe that these strategies are riskier than first thought once that, since industries drive much of the individual stock momentum returns, there is less diversification and more exposure to idiosyncratic risk across momentum strategies, being that stocks within the same industry are more highly correlated than those across different industries.

The original paper by Moskowitz & Grinblatt (1999) reported the average monthly profits for portfolios of winners minus portfolios of losers of individual equities (Raw strategy), representing an analysis of individual stock momentum. To account for industry components, industry effects were neutralized through three strategy constructions: Industry Neutral strategies, which rank stocks by past returns within industries to ensure intra-industry comparisons, excess-industry strategies, which rank stocks by past returns relative to their industry average, and cross-industry contrarian strategies, which pair losers from high-momentum industries with winners from low-momentum industries.

Each of these strategies and its average profitability give us a different angle on the role of industries on momentum. For instance, the Industry Neutral strategy forcibly buys and sells stocks within each industry, meaning that stocks from low and high momentum industries will be bought and sold simultaneously instead of only buying high industry momentum stocks and selling low industry momentum stocks, as might happen otherwise. In comparison to the 0,43% average monthly returns of the Panel A Raw individual momentum strategy, the decreased average monthly returns of 0,11% for the Panel C Industry Neutral strategy is evidence that once industry effects are removed momentum weakens. The Panel C Excess Industry strategy goes one step further by considering only the individual momentum in excess of the industry average momentum. In industries with high momentum averages, a considerable number of stocks will be left with very low or even negative momentum figures, making them not entering the pool of stocks to be bought or even making them enter the pool of stocks to be shorted. The negative -0,07% average monthly return for the Excess Industry strategy is also evidence that industries drive individual momentum, since momentum profits didn’t persist under this strategy. Finally, the High Industry Losers minus Low Industry Winners strategy allows us to understand if stock-specific momentum can defy industry trends by focusing on contrarian performers. Reporting an average monthly profit of 0,3%, this strategy reveals that a considerable portion of individual stock momentum returns (0,43% per month) is driven by industry components.

By replicating their methodological approach, expanding the analysis to a new sample period and to value strategies, this paper aims to determine whether industry composition drives the profitability of value-based strategies, as observed in momentum.

A total of four strategies were replicated both for the original sample period (July 1963 through July 1995) and for an extended sample period to include data up until 2023, as well as for the value-based strategies.

1.2.1 Results Comparison

While the original study identified a strong and persistent industry momentum effect, extending the dataset to include new data shows a gradual decrease of raw momentum returns, alongside a growing reliance on sector-level dynamics in explaining the anomaly.

These shifts reflect broader structural changes in financial markets, including the rise of quantitative strategies, macroeconomic volatility, and increased sector concentration, which have collectively reshaped the risk-return profile of momentum investing.

The declining profitability of raw momentum strategies emerges as a central theme. Initial findings demonstrated robust returns, but replications over identical periods report lower premiums, with extensions to more recent data further diminishing profitability. This pattern aligns with literature documenting factor decay, where widespread adoption of momentum-based strategies, along with improved market efficiency, diminishes opportunities.

Industry effects, however, remain a persistent driver of momentum. Strategies neutralizing sector exposures—by ranking stocks within industries—yield consistently smaller premiums compared to raw momentum, reaffirming Moskowitz & Grinblatt (1999) conclusion that industry-level momentum historically explained the anomaly.

Efforts to isolate stock-specific momentum by adjusting for industry averages produce inconsistent results, reflecting the fragility of firm-level momentum in modern markets. Early studies found such strategies negligible or counterproductive, while modern replications show premiums that vanish in extended samples.

In contrast, cross-industry contrarian strategies, which pair losers from high-momentum sectors with winners from low-momentum sectors, show higher returns over time.

Collectively, these results point to a gradual decrease of raw momentum returns, aligning with literature documenting factor decay, and a growing outperformance of industry momentum, potentially reflecting increased market concentration in industries such as technology and healthcare.

1.3 Value Premia and Industry Concentration

The rationale behind the HML anomaly formalized by Fama & French (1992) has competing interpretations of the value premium, according to the extant literature. The risk-based explanation, advocated by Fama & French (1996), states that high B/M (value) stocks are inherently riskier, often representing financially distressed firms or those with cyclical sensitivities, demanding higher expected returns as compensation for generating higher exposure to economic downturns or liquidity shocks. On the other hand, behavioral theories, advanced by Lakonishok et al. (1994), attribute the premium to investor mispricing, arguing that low B/M (growth) stocks become overvalued due to extrapolative expectations of past performance, while value stocks become undervalued due to an overreaction to stocks that performed badly, leading them to be underpriced.

This duality in perspectives has created a space for discussions among academics. For instance, Zhang (2005) proposed a hybrid model where value stocks' cash flows, being nearer term, expose them to cyclical risks, thereby joining risk and behavioral narratives.

Empirically, the HML factor demonstrated robust explanatory power in late 20th-century data. Fama & French (1993) showed that their three-factor model accounted for over 90% of cross-sectional return variation in U.S. equities with the value premium also persisting globally (Fama & French, 1998). Even though emerging markets exhibit stronger value premiums, likely due to informational inefficiencies, on U.S markets the profitability of value-based strategies has decayed in the 21st century, with the premium declining, even turning negative at times. This decline has been attributed to structural changes, such as the rise of the technological sector composed heavily by growth stocks (Hou et al., 2015), and increased factor crowding (Asness et al., 2013) diminishing profitability.

Following this shift in the nature of value premia, value-based investment strategies were adapted with advancements being made by academics. Hou et al. (2015) suggest incorporating different factor signals within strategies, combining value with quality or profitability metrics to offset industry-specific risks. Piotros's (2000) integrates financial health indicators with B/M ratios, improving value-strategies by filtering out distressed firms within high B/M industries. Similarly, Asness et al. (2013) provide empirical research on the improved efficiency of value strategies when applied globally and across asset classes.

Building investment strategies based on the value anomaly depends considerably on understanding how industry concentration affects its premium.

In this process, one has to consider the example of industries, such as utilities and manufacturing, which often carry high B/M ratios due to relying on capital-intensive business models, inflating value metrics without reflecting genuine mispricing. Furthermore, firms in structurally declining sectors may appear undervalued due to industry-wide underperformance rather than idiosyncratic undervaluation. Thus, analyzing the dependency of the profitability of value-based strategies on industry concentration requires establishing whether the value premium significantly relies on industry components by separating industry-level from firm-level drivers.

Moskowitz & Grinblatt’s (1999) framework is adapted to HML by replacing momentum’s return rankings with B/M ratios. Strategies under the same logic as explained previously are constructed, including Raw value (long high B/M, short low B/M stocks), Industry Neutral (ranking stocks by B/M within industries), Excess-Industry (adjusting stock B/M ratios by industry averages), and cross-industry contrarian strategies (pairing value stocks in low B/M industries with growth stocks in high B/M industries).

2. Data

A focus on the American stock market is evident and purposeful, being justified by the extensive data and academic research that are available.

The Center for Research in Security Prices (CRSP) was the main source to retrieve data on share prices, shares outstanding, security identifiers and Standard Industrial Classification (SIC) codes for common stocks listed on the NYSE, AMEX and Nasdaq, which compose the major U.S stock exchanges. Compustat was the main source to retrieve the accounting data, namely the book equity figures to compute the book-to-market ratios.

A number of filters were applied to the original dataset in order to ensure consistency and comparability of results, namely, only stocks with share code 10 and 11 were considered to build the strategies, representing ordinary common shares, and stocks with negative book-to-market ratios were filtered out of the value-based strategies. Furthermore, stocks with CRSP's missing return error codes[5] were filtered out of the sample.

The PERMNO and PERMCO variables extracted from CRSP were used as the unique identifiers to each security not changing during trading activity, after the security ceases trading nor with company name changes, making it possible to track securities throughout their trading history and preventing survivorship bias.

[5] Referring to error codes -66, -77, -88, and -99 due to stocks not trading on an exchange at time t or due to missing return values, for example.

2.1 Momentum Strategies' Data

For the initial replication of momentum, the sample ranges from July 1963 through July 1995, with this range being extended to the period from July 1926 through July 2023 on the strategies with an extended sample.

Table 2 reports the average monthly values for the momentum returns (based on the previous six months cumulative return), the number of stocks and percentage of total market cap for each industry portfolio for both the initial sample period (Replication) and for the extended sample period (Extension).

Industry portfolios were created by sorting stocks using the first two digits of the Standard Industrial Classification (SIC) code for each stock in order to maximize the coverage of the major stock exchanges, following Moskowitz & Grinblatt (1999).

The replication period shows an overall average momentum return of 7.35%, slightly declining to 7.20% in the extended sample, pointing towards momentum decay. The average number of stocks per industry decreased from 219.46 (replication) to 157.74 (extension), remaining well diversified. The "Other" category (miscellaneous sectors) dominated in scale, with replication-period stocks averaging 960.81 (declining to 774.87 in the extension) and showing a market cap surge from 17.14% to 36.86%, likely due to the rise of technology or unclassified growth sectors. Financials (SIC 60-69) maintained a stable market cap share (~17%) despite a drop in listed firms, while capital-intensive industries like Chemicals (SIC 28) and Utilities (SIC 49) retained relatively stable momentum returns and market influence. Smaller sectors such as Apparel (SIC 22-23) and Construction (SIC 32) saw diminished representation, with market caps below 1% in the extended period.

Industry	SIC	Avg. Momentum Returns		Avg. No. Of Stocks		Avg. % of Market Cap.	
		Replication	Extension	Replication	Extension	Replication	Extension
Mining	10-14	5,15%	5,87%	243,65	147,28	3,77%	2,45%
Food	20	7,53%	6,94%	123,71	92,67	3,88%	2,14%
Apparel	22-23	6,45%	6,01%	117,43	63,68	0,48%	0,16%
Paper	26	8,52%	7,87%	50,74	34,33	1,88%	0,55%
Chemical	28	7,88%	7,88%	204,34	181,95	10,97%	11,13%
Petroleum	29	8,23%	8,30%	35,30	30,87	5,57%	1,56%
Construction	32	6,72%	6,94%	54,80	30,92	0,60%	0,16%
Primary Metals	33	6,47%	7,27%	85,16	67,18	1,15%	0,36%
Fab. Metals	34	7,74%	7,67%	120,93	66,09	1,12%	0,44%
Machinery	35	7,19%	7,49%	282,41	178,18	6,45%	5,02%
Electrical Eq.	36	8,36%	8,32%	313,93	211,46	5,88%	5,86%
Transportation Eq.	37	7,52%	7,57%	104,05	85,55	3,53%	1,74%
Manufacturing	38-39	7,02%	7,34%	241,60	170,32	3,96%	3,58%
Railroads	40	9,25%	7,51%	18,95	27,88	0,41%	0,14%
Other Transport	41-47	6,98%	6,62%	85,23	62,30	0,99%	0,93%
Utilities	49	5,94%	6,40%	185,65	119,39	7,35%	3,04%
Dep. Stores	53	7,20%	7,38%	54,98	37,24	2,21%	1,07%
Retail	50-52, 54-59	6,94%	6,95%	393,49	269,53	5,46%	5,37%
Financial	60-69	7,50%	6,99%	712,09	503,10	17,18%	17,44%
Other	other	8,38%	6,71%	960,81	774,87	17,14%	36,86%
	Average	7,35%	7,20%	219,46	157,74	5,00%	5,00%

Table 1: Summary Statistics on the Momentum Strategies' Dataset

Summary statistics for the 20 momentum industry portfolios formed following two-digit CRSP Standard Industrial Code (SIC) for each individual security with share code 10 and 11. The portfolios are formed monthly for the original sample period in Moskowitz & Grinblatt (1999) from July 1963 until July 1995 (Replication) as well as for an extended sample period from July 1926 until July 2023 (Extension). The average monthly past six months cumulative returns (Avg. Momentum Returns) as well as the average monthly number of stocks and the average percentage of total market capitalization are reported for each industry portfolio and sample period.

2.2 Value Strategies’ Data

As for the dataset used to build the value strategies, the sample ranges from July 1970 until December 2023, with no earlier data being available due to the databases from which data was extracted by Eugene Fama and Kenneth French to compute value strategies not being available.

Table 4 reports the average industry monthly figures for B/M ratios, number of stocks in the dataset, and the average size of each industry in relation to whole dataset.

The value strategy dataset reports an overall average B/M ratio of 0.00096, with significant variation across sectors. Industries such as Railroads (SIC 40) exhibit the highest B/M ratio (0.0017), signaling potential undervaluation, while capital-light sectors like Chemicals (SIC 28) and Machinery (SIC 35) report lower ratios (0.0005–0.0007), aligning with growth-oriented valuations. The Financial sector (SIC 60-69) dominates in scale, averaging 858.86 stocks and 14.48% market cap, reflecting its overall importance. Niche sectors like Apparel (SIC 22-23) and Construction (SIC 32) show limited representation, with market caps below 1%. Utilities (SIC 49) and Primary Metals (SIC 33) maintain moderate ratios (0.0010–0.0012), consistent with stable, asset-heavy operations, while Retail (SIC 50-52, 54-59) and Transportation Equipment (SIC 37) show lower ratios (0.0009), possibly reflecting competitive or growth-driven pressures.

As happened with the momentum dataset, on the value dataset, the "Other" category (miscellaneous sectors) reports the highest market cap weight, averaging 1,302.23 stocks and 20.27% market cap, likely driven by unclassified or emerging industries.

Industry	SIC	Avg. B/M Ratio	Avg. No. Of Stocks	Avg. % of Market Cap.
Mining	10-14	0,0009	222,55	3,49%
Food	20	0,0009	103,10	4,01%
Apparel	22-23	0,0013	80,09	0,48%
Paper	26	0,0010	41,30	1,58%
Chemical	28	0,0005	272,98	10,76%
Petroleum	29	0,0009	26,10	5,87%
Construction	32	0,0011	36,55	0,52%
Primary Metals	33	0,0012	64,93	1,09%
Fabricated Metals	34	0,0009	90,56	0,98%
Machinery	35	0,0007	261,52	7,48%
Electrical Eq.	36	0,0007	333,60	6,13%
Transport Eq.	37	0,0009	92,14	3,50%
Manufacturing	38-39	0,0007	279,85	4,01%
Railroads	40	0,0017	11,26	0,58%
Other Transport	41-47	0,0010	86,61	1,15%
Utilities	49	0,0010	163,42	5,77%
Department Stores	53	0,0011	40,07	2,73%
Retail	50-52, 54-59	0,0009	428,83	5,11%
Financial	60-69	0,0010	858,86	14,48%
Other	other	0,0008	1302,23	20,27%
	Average	0.00096	239.83	5,00%

Table 2: Summary Statistics on the Value Strategies' Dataset

Summary statistics for the 20 value industry portfolios formed following two-digit CRSP Standard Industrial Codes (SIC) for each individual security with share code 10 and 11 and positive book-to-market ratios, with the book equity figures being sourced from Compustat. The portfolios are formed monthly from July 1970 until December 2023. The average yearly book-to-market ratio as well as the average monthly number of stocks and the average monthly percentage of total market capitalization are reported for each industry portfolio.

Professor Kenneth French's website[6] was consulted to extract data on strategies formed on book-to-market in order to have a benchmark of monthly figures for the average number of companies and the average monthly returns for value-based strategies.

When considering the 10th and 90th percentiles of book-to-market for forming the value strategies, a correlation of 92% and 97% was achieved between the monthly return figures stated by Professor Kenneth French and the figures computed on the factor extension Raw value strategy for the top 10% and bottom 10% of book-to-market stocks respectively, with the Professor stating an annualized return of 4,26% and the factor extension strategy figures stating an annualized return of 4,18% for the value strategies.

Metric	**Student**	**K. French**
Correlations		
Bottom 10	0,97	
Top 10	0,92	
Bottom - Top	0,84	
Average Returns		
Bottom 10	1,05%	0,94%
Top 10	1,40%	1,30%
Bottom 10 - Top 10	0,35%	0,35%
Annualized Excess Return	4,18%	4,26%
t-stat	1,80	1,79

Table 3: Pure Value Strategy Data Description

Table 3 reports correlation figures between average monthly returns, along with the average monthly returns figures, annualized excess returns and t-statistics for the pure value strategy built in this thesis and data sourced from Professor Kenneth French's website for pure value strategies. These correlation figures are reported for the lower 10% (Bottom 10) and upper 10%

[6] The data can be found on: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

(Top 10) of book-to-market ratio stocks with NYSE-based 10th and 90th percentile book-to-market ratio breakpoints employed.

3. Empirical Analysis

The following section presents the methodology and empirical results for testing the role of industry concentration in momentum and value premia. Replicating Moskowitz & Grinblatt's (1999) framework and extending it to value strategies, the analysis evaluates Raw, Industry Neutral, Excess Industry, and Cross-Sector Contrarian strategies using U.S. equity data.

3.1 Momentum Analysis

Being that the initial part of this thesis is dedicated to replicating the analysis conducted by Moskowitz & Grinblatt (1999), the focus is initially given to assessing whether industry components are driving the premium that is derived from momentum-based strategies, as captured by the momentum factor of the Carhart Four Factor model (Carhart, 1997).

3.1.1 Methodology

A strategy to extract the individual equity momentum premium will be created first followed by three strategies that neutralize industry components on the individual equity momentum. All the strategies on momentum have an intermediate investment horizon (six-to-twelve-month range), which represents the period for which momentum premium is strongest and are based on each stock's past six months cumulative returns to define momentum with a holding period of six months to compute portfolio returns. Every momentum strategy is composed of a new long/short portfolio combination that is opened monthly and rebalanced every six months as a result of ranking stocks on their past six months returns and holding them for six months. This implies that, for all the momentum strategies, each month's return for the overall strategy is composed by the returns of six different long/short portfolio combinations with a combination being opened or rebalanced monthly, following the methodology originally employed by Jegadeesh & Titman (1993).

3.1.1.1 Raw Momentum

This study first starts by analyzing the return of pure momentum strategies by replicating the first strategy, defined as Raw, from Panel A in the analysis by Moskowitz & Grinblatt (1999) for the original sample including data from July 1963 to July 1995.

A strategy of stocks is built to form a self-financing strategy composed of long positions on winners and short positions on losers in individual stocks, with the ranking being attributed according to each stock's past 6-month cumulative return with 30% breakpoints being employed to filter the stocks—i.e., highest 30% of momentum stock returns minus lowest 30% of momentum stock returns. Within the strategy, two new portfolios for long and short positions are opened every month and then held for the next six months to be rebalanced at the end of this period. The equally weighted returns are computed every month for every "live" long/short portfolio combination with the overall monthly strategy returns being composed of 1/6 of every "live" portfolio combination, as was explained earlier.

3.1.1.2 Industry Neutral

Industry components are first neutralized on the individual equity momentum premium with the Industry Neutral strategy following the first strategy on Panel C (Moskowitz & Grinblatt, 1999).

To form this strategy, stocks are first sorted into their respective industry groups according to their industry's first two Standard Industrial Classification code digits. Within each industry, the six months historical cumulative return is computed for each stock to define momentum and a sorting is made of the top 30% momentum returns that represent the long positions and the bottom 30% momentum returns that represent the short positions. The value weighted return is then computed of the top 30% minus the bottom 30% of stocks within the industry for a holding period of six months.

3.1.1.3 Excess-Industry

The Excess Industry Momentum strategy, following the second strategy from Panel C by Moskowitz & Grinblatt (1999), isolates stock-specific momentum effects by adjusting the individual stock cumulative past six months returns for each stock's industry average cumulative past six months returns. Individual stock momentum is thus expressed as the difference from this industry average, defined as excess momentum:

$$\text{Excess Momentum} = \text{Stock Momentum} - \text{Industry Avg. Momentum} \qquad (1)$$

Stocks are ranked based on these excess momentum values across the entire universe of stocks in the sample, with the top 30% (high excess momentum) assigned to the long portfolio and the bottom 30% (low excess momentum) to the short portfolio. This adjustment ensures the strategy captures momentum driven by firm-specific performance rather than sector-wide trends. For example, in a high-momentum industry, stocks underperforming in momentum relative their industry peers (negative excess momentum) may still be shorted despite the sector's overall strength. Portfolios are rebalanced monthly with a six-month holding period, and returns are value weighted.

3.1.1.4 High Industry Losers minus Low Industry Winners

The third strategy establishes a ranking of each industry's average past six months cumulative returns and forms a long position on the bottom 30% of stocks within the 3 best performing industries and a short position on the top 30% of stocks within the 3 worst performing industries within that past 6-month period. The equally weighted return of the bottom 30% from the winning industries minus the top 30% from the losing industries is then computed for a holding period of six months.

3.1.2 Results

Strategy	**Moskowitz & Grinblatt**		**Replication**		**Extension**	
	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
Raw Momentum	0,0043	(4,65)	0,0038	(2,14)	0,0030	(2,30)
Industry Neutral	0,0011	(1,01)	0,0023	(1,53)	0,0011	(0,95)
Excess Industry	-0,0007	(-0,83)	0,0003	(0,27)	0,0019	(1,66)
High Ind. Losers - Low Ind. Winners	0,0030	(2,66)	0,0089	(5,57)	0,0063	(5,96)

Table 4: Momentum Profits for Individual Equities and Industry Neutralizing Strategies

Table 4 reports momentum strategies' average monthly returns for the original paper by Moskowitz & Grinblatt (1999) as well as for the strategies built in this thesis based on the original sample period (July 1963 until July 1995) and on the extended sample period (July 1926 until July 2023). Raw Momentum represents pure value strategies built by forming a long position on the highest 30% of past six months return stocks (winners) and a short position on the lowest 30% of past six months return stocks (losers), with all portfolios being held for six months. As for the Industry Neutral strategy, stocks are sorted based on their past six months returns within each industry, forming a long position on the top 30% and a short position on the bottom 30% of stocks. The Excess Industry strategy ranks stocks based on their past six months returns in excess of their industry's average past six months return, forming a winners minus losers strategy based on 30% percent breakpoints. Lastly, industries are sorted based on their past six months returns and a long position is formed on the bottom 30% of past six months returns within the top three industries and a short position is formed on the top 30% of past six months returns within the bottom three industries to form the High Industry Losers minus Low Industry Winners strategy.

3.1.1.1 Raw Momentum

In the original study, the raw momentum strategy generated a statistically significant monthly premium of 0,43% (t-statistic = 4,65). However, as shown in Table 4, the replication for the same period (1963–1995) shows a diminished premium of 0,38% (t-statistic = 2,14), with statistical significance weakening considerably. Extending the sample from 1926 until 2023 further diminishes the raw momentum premium to 0,30% (t-statistic = 2,30), aligning with evidence of declining momentum efficacy in recent decades, potentially due to crowded trades or improved market efficiency.

3.1.1.2 Industry Neutral

Industry neutral strategies, which control for intra-sector momentum by ranking stocks within industries, prove the persistent role of industry effects. Moskowitz & Grinblatt reported a 0,11% premium (t-statistic = 1,11) for this strategy, statistically insignificant and a small fraction of raw momentum returns. The replication shows a higher average return of 0,23% (t-statistic =1,53), while the extended sample reports 0,11% (t-statistic = 0,95). Being statistically not significant, these results imply that intra-industry stock selection contributes minimally to momentum profits across all periods, further proving the importance of industry-level momentum.

3.1.1.3 Excess-Industry

The original study found non-significant returns (-0,07%, t-statistic = -0,83), whereas the replication shows a low positive premium (0,03%, t-statistic = 0,26). However, in the extended sample, excess-industry returns rise to 0,19% (t-statistic = 1,66), remaining statistically insignificant entirely. This suggests that stock-specific momentum, separated from industry trends, has remained somewhat unreliable in recent decades.

3.1.1.4 High Industry Losers minus Low Industry Winners

The High Industry Losers - Low Industry Winners strategies—pairing losers from high-momentum industries with winners from low-momentum industries—show increasing returns over time. Moskowitz & Grinblatt reported 0.30% monthly profits (t-statistic = 2,66) for this approach, but the replication nearly triples this premium (0,89%, t-statistic = 5,77), with even stronger results in the extended sample (0,63%, t-statistic = 5,96). This acceleration demonstrates the growing dominance of industry momentum in driving returns, particularly in modern markets. The rising t-statistics further signal that industry selection now explains a larger share of momentum.

3.2 Value Analysis

Following the overall same logic applied to momentum strategies, value-based strategies were constructed to assess whether industry concentration drives the profitability of value strategies.

3.2.1 Methodology

In order to extend the analysis first conducted by (Moskowitz & Grinblatt, 1999) on momentum to value strategies, the premium from value-based strategies for individual equities is first extracted to isolate the cross-sectional returns attributable to the book-to-market anomaly, followed by three strategies that neutralize industry components on the individual equity value. Following the work of Fama & French (1993) and the methodology provided by Professor Kenneth French's data library, value strategies were built to systematically capture the historical outperformance of high book-to-market stocks relative to low book-to-market stocks.

3.2.1.1 Raw Value

Building the pure value strategy, defined as Raw Value, starts with the calculation of the book-to-market ratio for each stock, defined as the book value of equity from fiscal year t-1 divided by its market value of equity, defined as the product of shares outstanding and share price, as of the end of June of year t to account for the lag in financial reporting and ensure that only publicly available information influences portfolio formation. Furthermore, all stocks with negative book-to-market (B/M) ratios were excluded from the sample.

NYSE-listed securities were used as the reference to compute standardized B/M breakpoints. Specifically, the 10th and 90th percentile B/M thresholds were derived exclusively from NYSE stocks, defining value and growth stocks across all exchanges (NYSE, AMEX, and Nasdaq). These NYSE-determined breakpoints were then applied to the broader database to classify stocks into deciles. The top 10% of high B/M stocks (value) and the bottom 10% of low B/M stocks (growth) were selected to form a self-financing strategy. The value weighted return of the top 10% of stocks minus the bottom 10% of stocks was computed with a holding period of one year, with the portfolios being rebalanced annually at the end of June with NYSE breakpoints being recalculated each year to define value and growth stocks.

3.2.1.2 Industry Neutral

To neutralize industry effects and isolate stock-specific value premia, the Industry Neutral Value strategy ranks stocks by their book-to-market ratios within their respective industries, defined by the first two digits of the Standard Industrial Classification (SIC) code. NYSE-based B/M breakpoints are calculated within each industry and then applied across all the exchanges to define value and growth stocks. Within each industry, the top 10% of high B/M stocks are assigned to the long portfolio, and the bottom 10% of low B/M stocks are assigned to the short portfolio. This intra-industry ranking ensures that the strategy buys and sells stocks across all sectors, rather than concentrating exposure to high-B/M industries. The value weighted returns are computed for a holding period of one year with the portfolio being rebalanced annually at the end of June using recalculated NYSE breakpoints, maintaining alignment Professor Kenneth French's framework and ensuring consistency with fiscal year-end data.

3.2.1.3 Excess Industry

The Excess Industry Value strategy adjusts each individual stock's B/M ratios by subtracting their industry's average B/M ratio, isolating stock-specific value effects from sector-wide trends.

For each industry, the average B/M ratio is computed, and each stock's B/M ratio is then expressed as a deviation from this industry average. Within all the stocks under NYSE, 10^{th} and 90^{th} percentile B/M breakpoints are calculated by ranking stocks based on these excess B/M values. These breakpoints are then applied to the broader sample, with the top 10% of high excess B/M stocks assigned to the long portfolio and the bottom 10% of low excess B/M stocks assigned to the short portfolio. This methodology tests whether value premia persist when separated from industry momentum. For instance, stocks with B/M ratios exceeding the sector average are prioritized, even if the sector itself has a low aggregate B/M ratio. Returns are value-weighted and rebalanced annually in June, with B/M breakpoints and industry averages recalculated each year to reflect evolving sector dynamics.

3.2.1.4 High Industry Growth minus Low Industry Value

The High Industry Growth minus Low Industry Value strategy adopts a contrarian approach by pairing value stocks in low-B/M industries with growth stocks in high-B/M industries. Industries are first ranked by their book-to-market ratios. The top three high-B/M industries and bottom three low-B/M industries are identified. NYSE-based B/M 10^{th} and 90^{th} percentile breakpoints are calculated and applied to the broader databased and a long position is formed within the high-B/M industries on the bottom 10% of stocks, while within the low-B/M industries, the top 10% of stocks are shorted, with this strategy testing whether industry trend effects can offset firm-specific value. For example, shorting low-B/M stocks in a high-B/M sector and longing high-B/M stocks in a low-B/M sector captures mispricing within industries. Returns are value weighted and rebalanced annually as of the end of June, with breakpoints recalculated yearly to align with fiscal year-end reporting.

3.2.2 Results

Strategy	Mean	(t-stat)
Raw Value	0.0035	1.80
Industry Neutral	0.0037	2.33
Excess Industry	0.0021	1.44
High Ind. Growth minus Low Ind. Value	0.0032	1.53

Table 5: Value Profits for Individual Equities and Industry Neutralizing Strategies

Table 5 reports the average monthly profits of high book-to-market stocks minus low book-to-market stocks for individual equities and industry neutralizing strategies based on a sample period that extends from July 1970 until December 2023. All strategies employ NYSE-based 10th and 90th percentile book-to-market breakpoints to stocks in the major exchanges to form long positions on high book-to-market stocks and short positions on low book-to-market stocks and compute value-weighted returns with a holding period of six months. Raw value represents a pure value-based strategy of high book-to-market minus low book-to-market stocks, with the top 10% of stocks and bottom 10% being selected from the pool of stocks resulting from employing the NYSE-based book-to-market breakpoints to form the self-financing strategy. As for the Industry Neutral strategy, NYSE-based book-to-market breakpoints are employed within each industry to filter the stocks and the top 10% form the long positions and the bottom 10% of stocks form the short positions within each industry. The Excess Industry strategy adjusts each stocks' book-to-market ratio according to its industry's book-to-market average, with NYSE-based breakpoints being employed to filter the stocks with the top 10% (high) and bottom 10% (low) of stocks forming the value strategy. Finally, industries are sorted based on their book-to-value ratios and, within the top 3 and bottom 3 industries, NYSE-based breakpoints are employed to form a long position on the bottom 10% of stocks in the top 3 industries and a short position on the top 10% of stocks in the bottom 3 industries.

3.2.2.1 Raw Value

As Table 5 shows, the Raw Value strategy generated a monthly premium of 0,35% (t-stat = 1,80), consistent with historical evidence of the value anomaly. However, the t-statistic falls short of significance thresholds (t-stat > 1,96), suggesting that the raw value premium, while economically meaningful, may be sensitive to industry-level clustering or decreased efficacy in modern markets. This aligns with recent literature documenting a global decline in the value premium, potentially due to crowded trades or structural shifts in market composition (e.g., growth-dominated sectors like Technology).

3.2.2.2 Industry Neutral

The industry neutral strategy produced a 0,37% monthly premium (t-stat = 2,33), achieving statistical significance at the 5% level. This result shows the robustness of stock-specific value effects independent of sector exposures. By neutralizing industry momentum, the strategy isolates firm-level mispricing or risk factors, supporting behavioral explanations (e.g., investor overreaction to firm distress) while challenging the notion that industry concentration fully explains the value premium.

3.2.1.3 Excess Industry

The excess industry strategy, which adjusts for sector-wide valuation trends, yielded a non-significant 0,21% premium (t-stat = 1,44). The lack of statistical significance implies that value premia separated from industry components are unreliable, reinforcing the interdependence of stock-level and sector-level effects.

3.2.1.4 High Industry Growth minus Low Industry Value

The High Industry Growth minus Low Industry Value strategy generated 0,32% average monthly returns (t-stat = 1,53), although these results lack statistical significance.

In the momentum strategy following the same rational, momentum profitability persisted despite the individual stock momentum components not being favorable (buying low momentum stocks and selling high momentum stocks), meaning that industry components rise over individual stock components in the momentum anomaly. However, the same was not observed for the value anomaly, implying that pairing value stocks in low-B/M sectors with growth stocks in high-B/M sectors fails to systematically exploit mispricing, with value profitability vanishing, thus it is concluded that industry components don't rise over stock specific components for the value anomaly.

4. Conclusion

This paper investigated the role of industry concentration in explaining the value premium, extending the methodology proposed by Moskowitz & Grinblatt (1999),originally applied to momentum, to evaluate whether industry dynamics influence the profitability of value-based strategies. By replicating the original methodology, expanding the sample period, and adapting the framework to value strategies, this research provides critical contributions to understanding the sources of abnormal returns in modern financial markets.

For momentum, the extended timeframe confirms the gradual decline in the average monthly profitability of pure momentum strategies, decreasing from 0,43% (1963–1995) to 0,30% monthly (1926–2023), aligning with literature on factor decay. However, industry effects remain persistent with strategies neutralizing sector exposures (e.g., Industry Neutral Momentum) showing statistically insignificant premiums, while cross-industry contrarian approaches (High Industry Losers minus Low Industry Winners) show rising returns (0,63% monthly, t-stat = 5,96). These results providence evidence to the fact that industrial concentration amplifies momentum's reliance on macro-level trends, reducing diversification benefits and exposing investors to idiosyncratic risks.

Applying the same framework to value strategies gives us different conclusions. The pure value strategy (Raw Value) generated a non-significant premium (0.35% monthly, t-stat = 1,80), but Industry Neutral versions (Industry Neutral Value) achieve robust statistical significance (0,37%, t-stat = 2,33). This difference suggests the value premium is less tied to sectoral trends, driven instead by firm-specific characteristics, such as financial distress or cyclical exposure. Excess-industry strategies (e.g., Excess Industry Value), however, show fragility (0,21%, t-stat = 1,44), while cross-industry approaches (High

Industry Growth minus Low Industry Value) fail to report significant returns (0,32%, t-stat = 1,53).

The divergence between factors provides grounds for distinct theoretical explanations. Momentum depends on industry-level trends amplified by market concentration, while value retains dependence on idiosyncratic components, consistent with risk-based narratives (e.g., distress premiums) or behavioral explanations (e.g., overreaction to negative news). For investors, these conclusions imply that they should be diligent with these strategies, given that momentum demands active management of sector exposures to mitigate concentration risks, while value benefits from rigorous intra-industry stock selection.

The study's limitations, such as its focus on U.S. data, exclusion of transaction costs, the usage of equally weighted returns on several momentum portfolios, and usage of the same investment horizon for the value strategies as was employed for momentum strategies which might not be optimal, open avenues for future research. Incorporating global data would test the generality of results while analyzing transaction costs and different investment horizons could assess the practical impacts of these variables on value strategy profitability. Additionally, integrating hybrid factors (e.g., quality, profitability) might clarify interactions between value and other anomalies.

In summary, this research demonstrates that industry concentration explains a significant portion of the momentum premium but not the value premium, further proving the need for different theoretical models to explain cross-sectional anomalies. For academics, the results emphasize the importance of separating sources of abnormal returns and, for practitioners, they point towards the relevance of sectoral adjustments in factor management. In an increasingly efficient market landscape, the ability to isolate specific drivers—whether sectoral or idiosyncratic—remains central to the pursuit of alpha.

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

During the preparation of my written work/thesis, "Does Industry Concentration Drive the Value Premium?", ChatGPT was used for the following tasks: data analysis in R and proofreading/increasing quality of writing, with the prompts used listed at the end of the document in the Prompts List section. After using this tool/service, I reviewed and edited the content as necessary and I am aware of and respect the Artificial Intelligence Rules of Conduct of Católica Porto Business School.

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Prompts list:

Filtering out return error codes:

"I have a table with return error codes that I filtered out of my sample. How can I efficiently remove these error codes from my dataset in R while keeping the rest of my data intact?"

Refining a sentence about investment horizons:

"Here's a sentence I wrote in my thesis: 'Moskowitz et al. (1999) used a 6-month formation and 6-month holding period for momentum strategies. Since momentum is strongest in the mid-term, this horizon is optimal for momentum, but value strategies may behave differently.' Improve its clarity and readability."

Managing duplicates on the dataset:

Can you give me a line of code that excludes PERMCO duplicates on top_30_ june?

Calculating value weighted returns:

I have this dataset that has the Market_Cap calculated per PERMCO per month. I want to calculate the weights every June and the fill onwards until May next year, and in next June calculate the new weights and so on.

Managing overlapping momentum portfolios (L6/H6):

"In my R code, momentum strategies use a 6-month formation and 6-month holding period (L6/H6), which implies having 6 overlapping strategies active at once. How can I structure my code to track each portfolio's lifecycle, calculate monthly returns for all active portfolios, and aggregate results without double-counting?"

Optimizing R code for portfolio construction:

"I need to calculate value-weighted returns for portfolios rebalanced annually. Here's my current R script: (attachment). Are there more efficient ways to handle lagged book-to-market ratios and the weightings?"

Improving computational efficiency for large datasets:

"My R script takes too long to process the returns of the momentum strategies. Suggest different techniques to speed up the process"

Calculating t-statistics for strategy returns:

"I need to compute t-statistics for my momentum strategy's monthly returns. What R packages should I use, and how do I implement this correctly?"

Addressing conflicting theories in literature review:

"The risk-based vs. behavioral explanations for the value premium contradict each other. How can I structure this section to fairly present both arguments while focusing on my study's contribution?"

Reframing sentences:

"My conclusion restates results without addressing broader implications. How can I reframe it to highlight contributions to market efficiency debates and practical investing?"