A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

FIELD LAB: ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

Sector-Based Credit Risk and Stock Returns

Analyzing the Dynamic Relationship Between Consumer Spending Patterns and Stock Market Sector Performance

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Abstract

This report combines two investment strategies from portfolios with a low correlation coefficient: the *Credit Risk* and the *Consumer* strategies. The *Equal-weighted*, *Tangency*, and *Minimum Variance Portfolios* were created and resulted in a well-balanced approach that can outperform the individual strategies. In the out-of-sample analysis, the *Minimum Variance Portfolio* not only exhibited lower volatility but also demonstrated superior risk-adjusted returns, a result contrary to the initial expectations set by the *Tangency Portfolio*. Furthermore, the *Equal Weighted* despite presenting higher returns exhibited the lowest risk-adjusted performance. Thus, these results allow investors to select the appropriate approach according to their preferences.

Keywords: Quantitative Investments, US Stocks Market, Financial Markets, Credit Risk, Consumer Behaviour, Consumer Spending.

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1. Introduction

Over the years, quantitative investment strategies have gained significant importance and have also become a fundamental component of modern investment practices. The rise of these strategies can be attributed to their proven reliability and efficiency in navigating complex financial markets. As investors seek to uncover hidden patterns and sources of alpha that generate abnormal returns, incorporating mathematical models and algorithms to identify investment opportunities has become advantageous and essential.

In this study, the *Sector-based Credit Risk and Stocks Return* strategy and the *Analyzing the Dynamic Relationship Between Consumer Spending Patterns and Stock Market Sector Performance* strategy are combined to create a diversified portfolio. A combined strategy can enhance overall portfolio performance as it leverages the strengths of diverse approaches mitigating risk through diversification and optimizing returns. Thus, the study aims to understand to which extent these diversified portfolios can outperform individual strategies in terms of risk-adjusted returns. Three portfolios with distinct construction methods and investment objectives are created: the *Equal-weighted*, *Tangency*, and *Minimum Variance* portfolios. These portfolios are then subject to rigorous analysis to provide a comprehensive evaluation of their performance shedding light on their advantages and limitations.

The study is organized as follows. In section two, the individual strategies are presented in more detail. Section three corresponds to the combined strategies, where it starts with a brief comparison of the individual strategies' performance, followed by the methodology to construct the diversified portfolios and the analysis of their results in an in-sample and out-of-sample period to test the consistency of their performance. Finally, we conclude in section four.

2. Individual Strategies

2.1. Sector-based Credit Risk and Stocks Returns

2.1.1 Economic Motivation

The Capital Asset Pricing Model (CAPM) serves as the foundational framework for the risk-return dynamics in finance as it asserts that investors should expect to be rewarded with higher returns for investing in riskier securities. However, several studies such as Dichev and Piotroski (2001) and Avramov et al. (2009) present compelling evidence of a negative relationship between credit risk and returns. This credit risk-return puzzle challenges the conventional understanding of the relationship between risk and returns proposed in traditional asset pricing models, as stocks with higher credit risk yield lower returns than lower credit risk stocks, suggesting that investors may not perceive securities with high credit risk as inherently risky. Thus, the study introduces a new perspective on the phenomenon, that sectors less exposed to economic cycles will tend to present stronger negative credit-risk return dynamics. For instance, defensive sectors, such as utilities and consumer staples, provide goods and services that are indispensable regardless of the economic conditions. The economic resilience of these sectors ensures a relatively constant demand for their products and services even during downturns. Consequently, investors may perceive high credit risk as less risky within these sectors. A better understanding of these dynamics may provide valuable insights into this phenomenon but can also offer valuable opportunities for investors seeking to refine and identify strategies.

2.1.2 Data & Methodology

The data for the monthly returns and S&P Domestic Long-Term Issuer Credit Rating was obtained from Compustat via the Wharton Research Database (WRDS). The Fama-French 3 monthly factors were achieved from the Ken French Website also via WRDS. These samples ranged from May 1987 to February 2017. In addition, the first level of the Global Industry

Classification Standard (GICS)[1] was chosen for sector analysis as it is a widely recognized system, and the credit ratings serve as a signal for the portfolios. Stocks with ratings classified as investment grade, equivalent to BBB- or better, are distinguished from those stocks categorized as high-yield or non-investment grade, equal to BB+ or worse.

Table 1 displays each sector's betas since this metric measures the sensitivity of a sector to the economic cycles. The higher the beta value, the greater the exposure to economic cycles. According to the results, while the defensive sectors, namely *Consumer Staples (30)* and *Utilities (55),* presented the lowest betas, the *Information Technology (45) and communication Services (50)* sectors presented the highest values.

Table 1: Sectors Betas

	Sector 10	**Sector 15**	**Sector 20**	**Sector 25**	**Sector 30**	**Sector 35**	**Sector 40**	**Sector 45**	**Sector 50**	**Sector 55**	**Sector 60**
Beta	0.997	1.201	1.183	1.267	0.758	0.932	1.004	1.642	1.354	0.373	0.886

To confirm the influence of the sector's exposure to economic cycles in stock performances a long-short portfolio that goes long on investment-grade stocks while shorting non-investment-grade stocks was created for each sector. The results will clarify whether, in sectors with lower betas, high-credit-risk stocks underperform those with low-credit-risk due to their lower perceived risk. According to these results, each month three best-performing sectors based on the average of the cumulative returns and the Sharpe ratio will be selected to compose the long-short and long portfolios. The portfolios start in May 1988 as a minimum of twelve months of historical data is used in the selection of the sectors to ensure the robustness of the process. Both portfolios take a long position on the investment-grade stocks of the best sectors, however, the long-short portfolio also takes a short position on the non-investment-grade stocks of these same sectors.

[1] The sectors and their GICS codes are as follows: *Energy (10), Materials (15), Industrials (20), Consumer Discretionary (25), Consumer Staples (30), Health Care (35), Financials (40), Information Technology (45), Communication Services (50), Utilities (55), Real Estate (60).*

2.1.3 Sector's Performance

Graph 1: Sectors Portfolios Cumulative Return

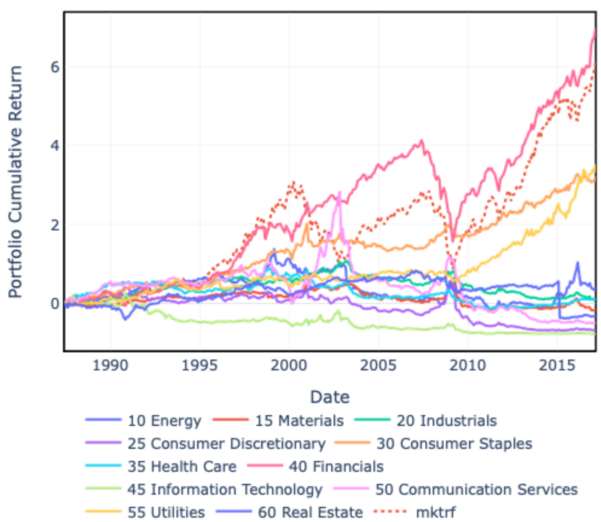


Table 2: Performance Metrics

FULL PERIOD			
Sector	**Annualized Return**	**Annualized Volatility**	**Sharpe Ratio**
10	0.011	0.137	0.082
15	-0.007	0.087	-0.078
20	0.003	0.071	0.039
25	-0.038	0.138	-0.276
30	0.049	0.075	0.660
35	0.003	0.079	0.039
40	0.072	0.109	0.661
45	-0.050	0.168	-0.299
50	-0.023	0.177	-0.131
55	0.052	0.086	0.602
60	-0.013	0.149	-0.089
mktrf	0.064	0.152	0.420

For a robust analysis of the sectors, Graph 1 shows the cumulative returns of the sectors' portfolios in comparison to the market, while Table 2 presents additional performance metrics. The results suggest that the *Financials (40), Consumer Staples (30),* and *Utilities (55*) sectors, are the ones with the strongest performance and consequently the highest annual returns. It is also possible to observe that despite the *Financials (40)* being the only portfolio to overperform the market in terms of cumulative returns, all three sectors have high Sharpe ratios, and therefore are the only ones able to overperform the market in terms of risk-adjusted returns. Conversely, all the other sectors presented weaker and diminishing performances, leading some sectors to display negative cumulative. The *Consumer Discretionary (25)*, *Information Technology (45)*, and *Communication Services (50*) sectors presented the lowest Sharpe ratios, the lowest annual returns, and the highest volatilities. The robust performances of defensive sectors and the weak performances of sectors with high beta confirm that indeed the exposure of the sectors to economic cycles may influence the way investors might perceive high credit-risk stocks.

2.1.4 Portfolios' Performances

Graph 2: Portfolios Cumulative Returns

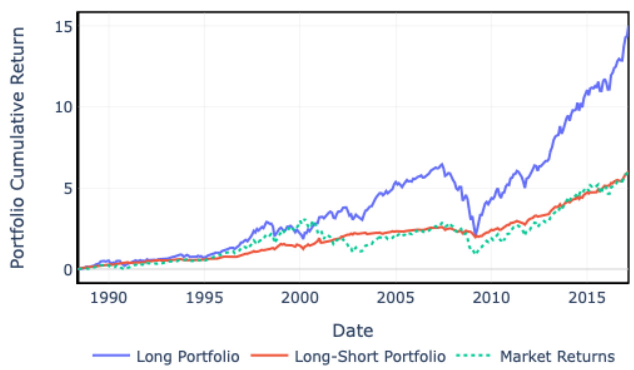


Table 3: Portfolios Performance metrics

FULL PERIOD			
	Long	**Long Short**	**Mkt-rf**
Return	0.101	0.07	0.071
Volatility	0.144	0.063	0.146
Sharpe ratio	0.702	1.118	0.484

*Returns and Volatility are in annualized terms

Building upon the insights from previous findings Graph 2 presents the cumulative returns of the long-short and long-only portfolios, alongside the market cumulative return, while Table 3 displays its performance metrics. The results indicate that in terms of cumulative returns, the long-only strategy effortlessly outperformed the market, whereas the long-short strategy exhibited only marginal outperformance relative to the market. However, it is important to highlight the superior volatility in the long-only portfolio, with an emphasis on the crisis of the 2008 downturn. While the long-short portfolio can keep a more stable performance it can outperform not only the long portfolio in terms of the Sharpe ratio but the market as well.

Table 4: FF3 Regression

	FULL PERIOD		FIRST HALF		SECOND HALF	
	Long	**Long Short**	**Long**	**Long Short**	**Long**	**Long Short**
Alpha	0.002	0.004	0.002	0.005	0.002	0.003
	(1.960)	(5.519)	(1.211)	(4.416)	(1.372)	(3.196)
Mkt-Rf	0.888	0.235	0.923	0.198	0.861	0.267
	(38.383)	(13.128)	(23.236)	(6.649)	(28.163)	(11.048)
SMB	-0.071	-0.235	-0.077	-0.267	0.013	-0.159
	(-2.269)	(-9.692)	(-1.745)	(-8.068)	(0.251)	(-3.752)
HML	0.524	0.158	0.574	0.139	0.465	0.092
	(15.601)	(6.083)	(10.045)	(3.249)	(9.753)	(2.436)
IR	0.045	0.226	0.046	0.257	0.037	0.183

* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

Table 4 shows the Fama-French Three Factor Model (FF3) regression of the full period, the in-sample, and the out-of-sample. In the full period, both strategies presented significant positive alphas, indicating an outperformance relative to the factors. The portfolios also have a statistically significant negative SMB and positive HML suggesting that, on average, the strategies tend to overperform when investing in larger stocks and value stocks. In addition, they also presented excess returns on a risk-adjusted basis when compared to the benchmark. When expanding the analysis to in-sample and out-of-sample, the long-short portfolio presents similar results under all three scenarios, with no significant changes in values. Conversely, the long-only portfolios show significant variations during both the first and second halves when compared to the full period. The main distinctions correspond to the long portfolio's alpha and SMB components that are not significant, suggesting no evidence of outperformance that cannot be explained by the factors and that there is no observed difference in returns between small-cap and large-cap stocks. All in all, the results indicate that despite both portfolios presenting consistency in results between in-sample and out-of-sample analysis, the long-short portfolio, overperforms market expectations, presenting lower volatility, and higher risk mitigation potential. Thus, the long-short portfolio is more fitting to offer superior diversification benefits in a combined strategy, hence its selection.

2.2 – Analyzing the Dynamic Relationship Between Consumer Spending Patterns and Stock Market Sector Performance

2.2.1 Economic Motivation

Consumer spending is a pivotal force driving economic growth, serving as a barometer for the overall health of an economy. The exploration delves into the dynamic relationship between consumer spending and the sectors of the stock market, examining whether discernible patterns exist and the potential implications for investors.

This metric represents a significant component of the gross domestic product (GDP) of the United States, close to 70%. As individuals purchase goods and services, businesses flourish, leading to increased revenue, job creation, and ultimately economic expansion. Consequently, fluctuations in consumer spending can have far-reaching consequences, affecting various sectors and industries. The behavior of consumers is influenced by a myriad of factors, including income levels, employment rates, inflation, interest rates, and overall economic sentiment.

This study observes that patterns in consumer spending may be linked to stock market movements. For example, during periods of robust economic growth, consumers may exhibit increased confidence, leading to higher spending and potentially contributing to a bullish stock market. Conversely, economic downturns may prompt consumers to tighten their expenditures, resulting in reduced spending and a bearish market.

2.2.2 Data & Methodology

Several economic indicators are closely monitored for insights into consumer behavior and, by extension, potential stock market movements. In this research, the Census Bureau possesses a comprehensive dataset on the Monthly Retail Trade Survey (MRTS) dating back to 1951, with the most robust working dataset initiated in February 1992. This survey captures a broad spectrum of nationwide establishments monthly, with results published 1.5 months later. The specific focus on signaling changes in General Merchandise Stores (452) arises from their sensitivity to shifts in consumer behavior. In prosperous economic conditions, consumers tend to escalate spending on non-essential items, positively influencing the sales and profitability of these stores. Conversely, economic contractions or uncertain periods may prompt reduced spending on discretionary goods, impacting the performance of such establishments.

Building on the findings of the Gupta, Leung, and Roscovan (2022) paper, which utilized a private dataset spanning 2013 to 2019, it exhibited a strong 90% correlation with the MRTS signal 452 – General Merchandise Stores, yielding a remarkable 16% net annual return for the consumer discretionary sector (equivalent to this paper's Durable sector) over seven years, we seek to extend and backtest the impact of the MRTS signal on a larger timeframe—from 1992 to 2023. This broader analysis encompasses all 12 Industry portfolios from the Kenneth R. French Library, aiming to discern if the MRTS signal can effectively indicate trends and subsequent returns across diverse sectors in the market.

In pursuit of higher diversification, a Long-Short portfolio is constructed, taking long positions on positive signals and short positions on negative signals for all 12 Industry portfolios. This approach diverges from earlier methodologies that, under tercile portfolios, went long on improving sales of individual stocks in the Consumer Discretionary sector and short on worsening ones. The Long-Short portfolio across various industries is designed to capture a more comprehensive market trend, offering insights into the nuanced impact of the MRTS signal on diverse sectors over an extended temporal horizon.

2.2.3 Sector's Performance

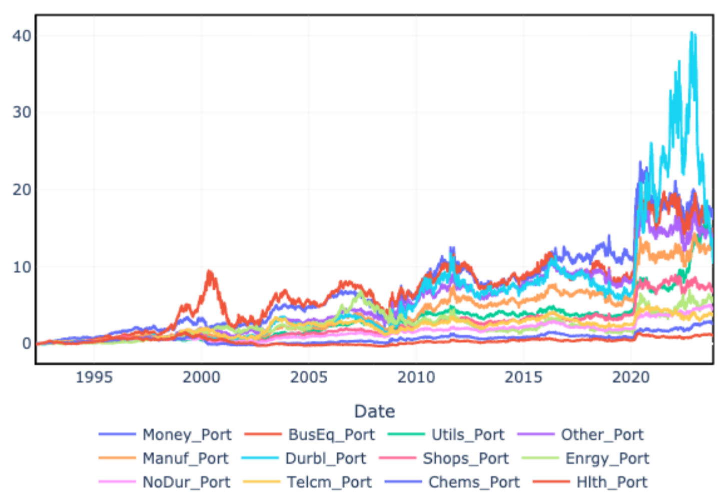
Table 5: Performance Measurements

Full Period			
Sector	**Annualized Return**	**Annualized Volatility**	**Sharpe Ratio**
NoDur	6.57%	14.88%	0.441
Durbl	11.69%	27.96%	0.418
Manuf	10.35%	20.83%	0.497
Enrgy	9.44%	26.54%	0.356
Chems	5.67%	17.68%	0.32
BusEq	11.94%	25.95%	0.46
Telcm	7.03%	20.12%	0.35
Utils	10.09%	17.44%	0.579
Shops	8.39%	18.85%	0.445
Hlth	3.95%	18.26%	0.216
Money	12.14%	24.70%	0.492
Other	10.47%	19.91%	0.526
Market	8.81%	18.52%	0.475

Within a 32-year timeline, the results highlight that the *Durables*, *Business Equipment,* and *Money* sectors delivered the most substantial annual returns. When considering risk-adjusted performance through the Sharpe ratio, the *Money*, *Manufacturing*, *Others*, and *Utilities* sectors outperformed the *Market* with higher values. The *Utilities* sector stands out as having both strong returns and lower volatility, contributing to its higher Sharpe ratio.

In contrast, the *Health*, *Chemicals*, *Non-Durables*, *Telecommunications*, and *Shops* sectors were the only ones to fall short of the *Market* in terms of annual returns. This underperformance was notably pronounced in the *Health*, *Chemicals*, and *Telecommunications* sectors, which displayed the lowest Sharpe ratios among the sectors analyzed.

Graph 3 – Cumulative Returns of the 12 Industries



Certain sectors exhibited an advantage in terms of risk mitigation, specifically, the *Non-Durables*, *Utilities*, *Chemicals*, and *Health* demonstrated lower volatility compared to the *Market*.

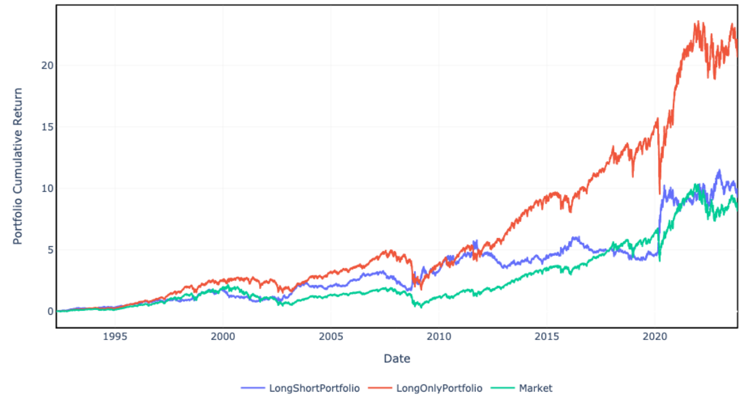
2.2.4 Portfolios' Performances

Table 6: Performance Measurements

Full Period			
Portfolio	**Annualized Return**	**Annualized Volatility**	**Sharpe Ratio**
Long Short	8.98%	17.51%	0.513
Long-Only	11.35%	17.50%	0.649
Market	8.81%	18.52%	0.475

The Long-Only portfolio outperforms both the Long-Short and Market portfolios in terms of annualized return and risk-adjusted performance, as indicated by its higher Sharpe ratio.

Graph 4 – Cumulative Returns of the Long-Short, Long-Only and Market



With a focus on exclusively taking long positions, this strategy delivers superior returns while maintaining a favorable risk-return balance. On the other hand, the Long-Short portfolio, designed to navigate both upward and downward market trends, exhibits a similar level of risk, but the return is much lower. The Market portfolio falls behind both in terms of returns and risk-adjusted performance.

3. Combined Strategy

3.1. Individual Strategies Comparison

Graph 5: Strategy Portfolio Comparison

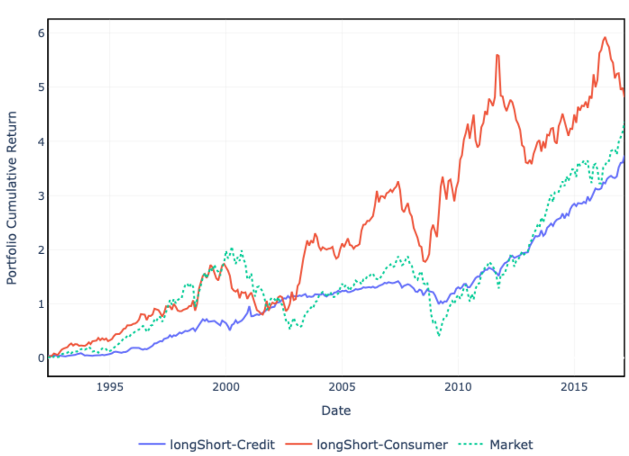


Table 7: Portfolios Performance metrics

FULL PERIOD			
	Credit Risk	**Consumer**	**Market**
Return	6.44%	7.32%	6.97%
Volatility	6.27%	14.33%	14.64%
Sharpe Ratio	1.028	0.511	0.476

*Returns and volatility are in annualized terms

In the combined setting, the previously used daily data of the *Consumer* strategy had to be transformed into monthly returns to adjust to the nature of the *Credit Risk* strategy. In addition, the strategies were shortened from April 1992 until February 2017 to accommodate the time frame of both. Under these settings, Table 7 displays the performance metrics of the portfolios. Despite the *Credit Risk* strategy exhibiting lower annual returns and volatility, than the *Consumer* strategy, it displays a higher Sharpe ratio. The cumulative returns for both strategies and the market are plotted in Graph 5. The *Consumer* portfolio while displaying a superior level of volatility with larger swings compared to the *Credit Risk* portfolio, concurrently presents a higher cumulative return and can overperform the market.

3.2 Methodology

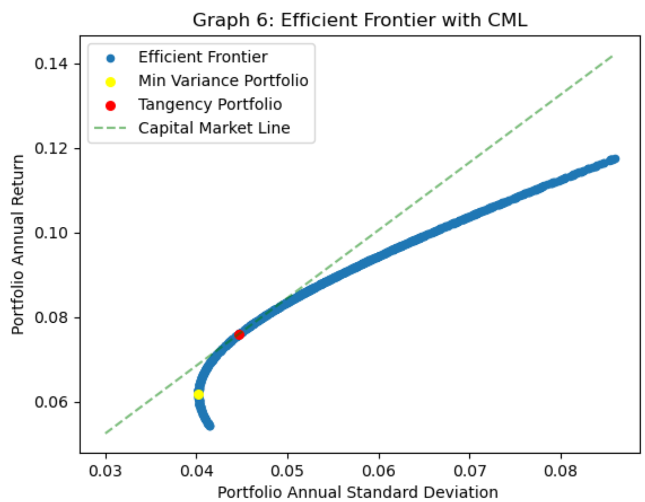
The individual strategies have independently showcased excellent performances, prompting an exploration into combining their strengths. The pursuit of constructing a portfolio that optimizes returns for a given level of risk led us to integrate the previously presented long-short individual strategies, creating a synergistic approach that harnesses the unique advantages of both *Credit Risk* and *Consumer* strategies. The rationale behind this combination is that the robust points of one strategy can mitigate the vulnerabilities of the other. By diversifying across both *Credit Risk* and *Consumer*, the portfolio aims to encompass a wider spectrum of market dynamics, with a focus on achieving superior risk-adjusted returns.

The correlation coefficient of 0.11 between the two strategies stands at an impressively low. This suggests that the strategies tend to move independently of each other, thereby fostering a high level of diversification and risk mitigation as the individual strategies are less likely to experience synchronized adverse movements. In addition, it makes the portfolio to be better positioned to navigate varying market conditions, offering a more resilient and balanced investment approach.

Recognizing that each strategy only includes equity, we consider each one, along with its respective returns, as an individual asset that becomes a component of a diversified portfolio. As such, three diversified portfolios to combine both strategies were created and analyzed: an *Equal-weighted Portfolio* (EW), a *Tangency Portfolio* (TP), and a *Minimum Variance Portfolio* (MVP).

The first diversified portfolio, the *Equal-weighted Portfolio* (EW), consists of assigning a weight of one-half for each individual strategy. This approach ensures an unbiased distribution of capital, providing equal importance to each in the overall portfolio allocation.

To obtain the *Tangency Portfolio* (TP) and the *Minimum Variance Portfolio* (MVP), we applied the principles of Markowitz's Portfolio Theory developed in 1952. The primary goal is to maximize expected return while minimizing risk. According to the theory, investors can select a portfolio that strikes an optimal balance between these two elements. Therefore, the efficient frontier in Figure 6 was constructed through a Monte Carlo simulation involving ten thousand portfolio weight combinations. Since this simulation generated diverse risk-return profiles, representing portfolios that maximize returns for each level of risk, minor variations in results are expected.



The *Tangency Portfolio* is situated at the intersection of the Capital Market Line (CML) and the Efficient Frontier and is represented in the same graph in red. The objective of this portfolio is to maximize the Sharpe ratio, achieving the highest possible return for a given level of risk. Conversely, the *Minimum Variance Portfolio* corresponds to the yellow dot on the Efficient Frontier offering the lowest volatility while remaining efficient, in other words, it aims to attain the lowest achievable level of risk.

To mitigate the impact of look-ahead bias on reported results, we conducted an initial analysis using the in-sample period, encompassing the first 5 years of returns from April 1992 to

April 1997. During this interval, we calculated the appropriate weights for both the *Tangency* and the *Minimum Variance Portfolios*. The TP allocated 65.8% to *Credit Risk* and 34.2% to the *Consumer* strategy, while the MVP had 88.1% in the former and 11.9% in the latter. This rigorous approach ensures that our analysis is rooted in historical data that was known at the time of decision-making, preventing any unintentional incorporation of future information.

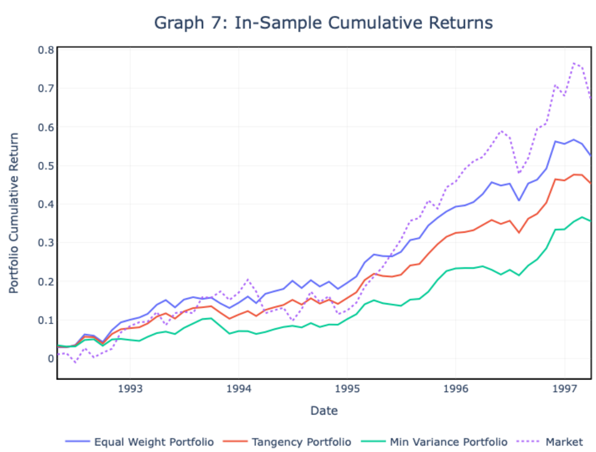
Having established the in-sample period, we then proceeded to the out-of-sample evaluation over the subsequent 20 years, spanning from 1997 to 2017. In this phase, we conducted a comparative analysis, assessing the performance of the *Equal-weighted, Tangency,* and *Minimum Variance Portfolios* against the market portfolio. This comprehensive examination allows for a robust assessment of the portfolios' effectiveness, providing insights into their real-world performance and resilience beyond the initial training period.

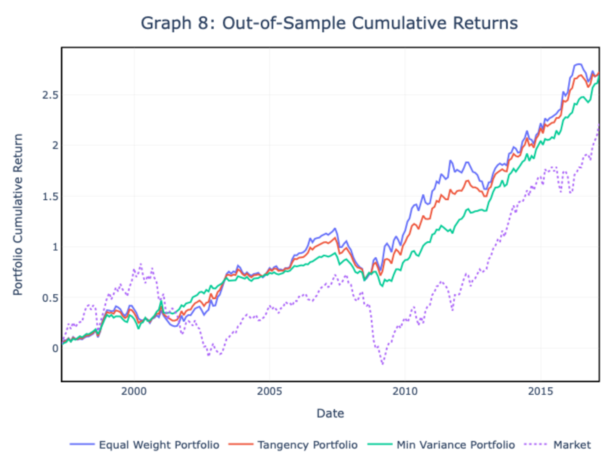
3.3 Results

3.3.1 Performance metrics

Table 8: Combined Portfolios Performance Metrics

	IN-SAMPLE				OUT-OF-SAMPLE			
	Equal	**Tan.**	**Min.**	**Mkt**	**Equal**	**Tan.**	**Min.**	**Mkt**
Return	8.79%	7.75%	6.26%	10.77%	6.78%	6.82%	6.78%	6.04%
Volatility	5.15%	4.42%	3.99%	9.04%	8.71%	7.21%	6.35%	15.73%
Sharpe Ratio	1.706	1.752	1.572	1.191	0.778	0.947	1.067	0.384





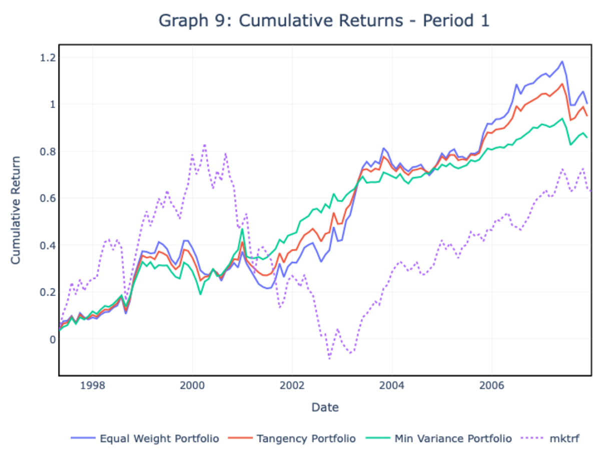
In the in-sample, the weights assigned during this period remain consistent in the subsequent out-of-sample phase. Despite the inherent forward-looking bias in this approach, it provides insights into the performance of the previously calculated optimal weights during the designated time frame. Hence, Table 8 shows performance metrics for portfolios and the market in both periods, while Graphs 7 and 8 display their cumulative returns, enhancing the analysis. Surprisingly, over these five first years, all three portfolios exhibited annual returns and annual volatilities lower than the market. Yet, as their volatility remained remarkably low, it resulted in extremely high Sharpe ratios for all three combined portfolios, indicating excellent risk-adjusted returns. When it comes to the cumulative returns, all three portfolios beat the market, the *Equal-weighted Portfolio* had the highest value at the end of the in-sample with 52.36%, and the *Minimum Variance Portfolio* with the lowest at 35.47%.

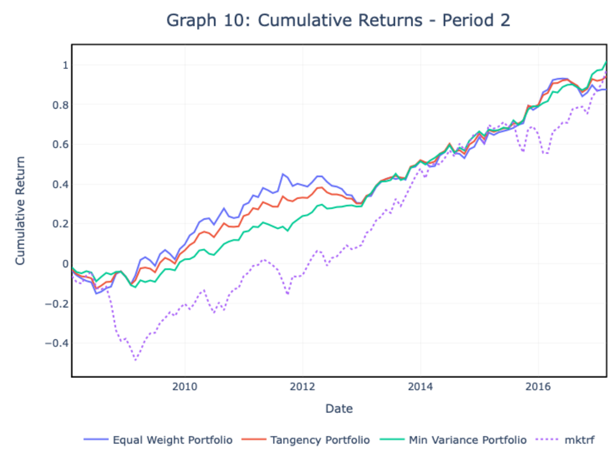
In the out-of-sample analysis, which encompasses the next 20 years, the annual returns of the three portfolios were closely contested and higher than those achieved by the market. However, the *Minimum Variance Portfolio* stood out due to its distinctive characteristic: its Sharpe ratio is the only one that exceeded 1. This implies that, for an equivalent level of returns, the *Minimum Variance Portfolio* is preferable due to its lower volatility. The cumulative returns were stable throughout the sample, with only a brief underperformance compared to the market in the initial years before the dot-com crisis. By the beginning of 2017, all three portfolios surpassed a cumulative return of 250%, while the market had only achieved 200%.

Finally, dividing the out-of-sample period into two distinct phases enhances the robustness of the analysis, allowing for the evaluation of portfolios across different market conditions, and economic landscapes, especially during pivotal events or crises. Segmentation facilitates a more granular understanding of a portfolio's adaptability, effectiveness, and resilience across different market environments, offering valuable insights into consistency.

Table 9: Out-of-Sample Performance Metrics

	PERIOD 1				PERIOD 2			
	Equal	**Tan.**	**Min.**	**Mkt**	**Equal**	**Tan.**	**Min.**	**Mkt**
Return	6.72%	6.45%	5.97%	4.76%	7.10%	7.51%	7.96%	7.71%
Volatility	8.82%	7.47%	6.72%	15.48%	8.60%	6.89%	5.88%	16.07%
Sharpe Ratio	0.762	0.864	0.888	0.308	0.826	1.089	1.354	0.480





Therefore, while Table 9 presents their performance metrics, Graphs 9 and 10 show their cumulative returns. For the period culminating in December 2007, annual returns, while modest, surpassed market averages, indicating a positive performance trend. Notably, volatility levels during this period were subdued, registering below market benchmarks. This dual dynamic of higher returns and lower volatility culminated in elevated Sharpe ratios, outperforming the market's metrics. All portfolio's cumulative returns, by 2007, were higher than those achieved by the market.

In the subsequent period commencing in January 2008, annual returns increased, with the *Minimum Variance Portfolio* leading in terms of returns, and with its lower volatility, it had the highest Sharpe ratio. The *Equal-weighted* and the *Tangency Portfolios* despite presenting similar returns, display slightly higher volatilities allowing them to have respectably high Sharpe ratios. While the market displayed a cumulative return consistent with all portfolios, it's worth noting that the market presented higher volatility,

3.3.2 CAPM regression

Table 10: CAPM Regression

	IN-SAMPLE			OUT-OF-SAMPLE		
	Equal Weights	**Tangency**	**Min. Variance**	**Equal Weights**	**Tangency**	**Min. Variance**
Alpha	0.005	0.004	0.004	0.005	0.005	0.005
	(2.611)	(2.737)	(2.474)	(3.102)	(3.749)	(4.253)
Beta	0.272	0.229	0.167	0.144	0.155	0.170
	(4.148)	(4.029)	(3.108)	(4.140)	(5.518)	(7.142)
IR	0.315	0.333	0.315	0.196	0.231	0.252

* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

The CAPM regression for the in-sample and out-of-sample are displayed in Table 10. Under the model, all portfolios exceeded expectations, displaying statistically significant alphas between 0.4% and 0.5%. Although their market betas are small and positive, they are statistically significant in both samples, indicating a tendency to move in the same direction as the overall market. The information ratios (IR), while small and higher in the in-sample, remain positive in the out-of-sample, suggesting that the portfolios outperformed the benchmark. Thus, the in-sample and out-of-sample results suggest consistent portfolio values, despite varying time lengths.

3.3.3 FF3 Regression

Table 11: FF3 Regressions

	IN-SAMPLE			OUT-OF-SAMPLE		
	Equal Weights	**Tangency**	**Min. Variance**	**Equal Weights**	**Tangency**	**Min. Variance**
Alpha	0.004	0.004	0.003	0.005	0.005	0.004
	(2.067)	(2.157)	(1.995)	(3.138)	(3.885)	(4.805)
Mkt-Rf	0.295	0.254	0.196	0.175	0.194	0.220
	(4.178)	(4.326)	(3.937)	(4.997)	(7.143)	(10.706)
SMB	-0.057	-0.122	-0.215	-0.138	-0.160	-0.190
	(-0.657)	(-1.697)	(-3.514)	(-2.902)	(-4.335)	(-6.814)
HML	0.056	0.046	0.033	0.066	0.107	0.165
	(0.597)	(0.595)	(0.496)	(1.310)	(2.751)	(5.609)
IR	0.271	0.274	0.238	0.195	0.225	0.239

* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

Table 11 displays the regressions for the Fama-French Three-Factor Model (FF3) for the in-sample and out-of-sample. It is possible to observe that under both scenarios, all portfolios presented positive and significant alphas despite them being very small, suggesting an overperformance ranging from 0.3% to 0.5% of what the factors predict. A noteworthy distinction between the two scenarios lies in the significance of the Small Minus Big (SMB) factor. In the first scenario, SMB is only statistically significant for the *Minimum Variance Portfolio*, while in the second scenario, all portfolios exhibit negative and significant SMB signifying the outperformance of larger companies over smaller ones. Similarly, the High Minus Low is not significant under any portfolios in the in-sample and is significant only for the *Tangency* and the *Minimum Variance* in the out-of-sample. These discrepancies may be attributed to the differing time lengths between the two scenarios. The extended period in the second scenario likely contributes to more robust results, increasing the reliability of detecting significant results for the SMB and HML across all portfolios. The information ratio (IR) suggests that all the portfolios are attractive as they generate positive excess returns relative to the benchmark.

Table 12: Out-of-Sample FF3 Regressions

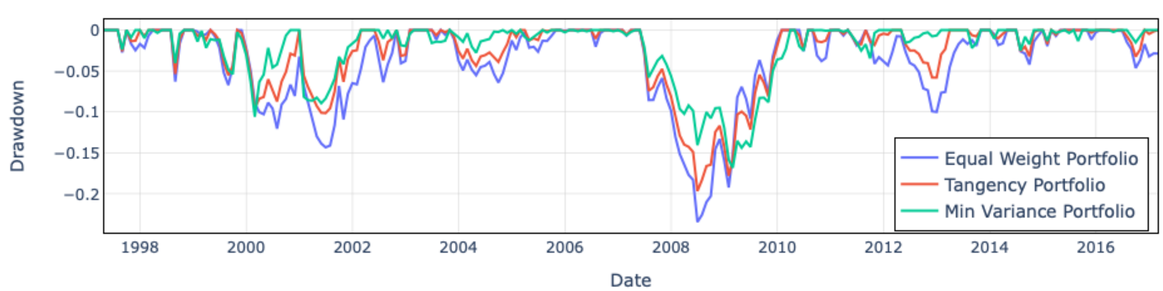
	PERIOD 1			PERIOD 2		
	Equal Weights	**Tangency**	**Min. Variance**	**Equal Weights**	**Tangency**	**Min. Variance**
Alpha	0.004	0.004	0.004	0.006	0.006	0.005
	(2.076)	(2.420)	(2.697)	(2.522)	(3.141)	(4.106)
Mkt-Rf	0.270	0.252	0.227	0.065	0.132	0.228
	(5.264)	(6.138)	(6.840)	(1.164)	(3.119)	(7.611)
SMB	-0.115	-0.144	-0.185	-0.204	-0.187	-0.164
	(-2.108)	(-3.297)	(-5.256)	(-1.914)	(-2.311)	(-2.864)
HML	0.099	0.139	0.197	0.199	0.164	0.115
	(1.359)	(2.399)	(4.207)	(2.295)	(2.490)	(2.473)
IR	0.170	0.187	0.187	0.236	0.279	0.302

* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

Again, the out-of-sample is divided into two periods in Table 12. In the first period, the results demonstrate consistency with only minor value changes compared to the full out-of-sample period. However, significant discrepancies become apparent when analyzing the second period more precisely, on the *Equal-weighted Portfolio* factors. Both the market and SMB components are non-significant, suggesting that the observed returns are not significantly influenced by changes in the market and by differences in returns between small and large stocks. In addition, the HML is positive and significant in period two, indicating a preference for value stocks in the portfolio. However, despite these differences and the lack of consistency when compared to the *Tangency* and the *Minimum Variance Portfolio*, the *Equal-weighted Portfolio* continues to present a positive IR indicating that it continues to generate risk-adjusted returns that surpass the benchmark.

3.3.4 Drawdowns

Graph 11: Portfolios Drawdowns



Graph 11 exhibits the drawdowns of the three combined portfolios, illustrating their peak-to-trough decline. This visualization provides insights into the magnitude of the strategy's potential losses, risks, and the time it takes for them to recover. The results confirm that despite the difference in assigned weights, the portfolios are exposed to similar downside risks. The *Equal-weighted* (EW), *Tangency* (TP), and *Minimum Variance* (MVP) *Portfolios* exhibit maximum drawdowns of -23.5%, -19.7%, and -16.8%, respectively. Yet, the highest peak for the MVP does not coincide with those of the other two portfolios. Thus, the MVP portfolio is the one that offers the greatest resistance against downside risk, while the EW is the one with the worst drawdowns.

4. Conclusion

All in all, the results demonstrate that combining the *Credit Risk* and *Consumer* strategies, besides exemplifying a dynamic and resilient investment approach that has consistently outperformed the market has the potential to improve the performance of the individual strategies in risk-adjusted terms. The effective diversification and risk mitigation within the combined portfolio due to the low correlation between the two individual portfolios is remarkably more advantageous to the *Consumer* strategy as lower volatility is also attained.

The construction of the three diversified portfolios resulted in a well-balanced investment approach that not only surpassed market performance but also demonstrated versatility. The *Equal-Weighted Portfolio* excelled in returns; however, it offers greater volatility and downside risk, resulting in the worst risk-adjusted performance in the out-of-sample. The *Minimum Variance Portfolio*, despite presenting the worst performance out of the three strategies on the in-sample, in the out-of-sample unveiled as the standout performer, exhibiting the highest risk-adjusted returns, higher information ratios, and lower downside risk. This suggests that the goal of achieving the lowest volatility to generate better performance was attained, however, different time lengths have a notable impact on its results. On the other hand, in the *Tangency Portfolio* the weights to generate the greater performance in terms of risk-adjusted returns, are not consistent throughout time, resulting in the worst performance in the out-of-sample than the MVP. In other words, the TP is not able to keep its goal and does offer the highest risk-adjusted performance in the out-of-sample.

In conclusion, the combined portfolios offer a compelling investment approach by leveraging the strengths of *Credit Risk* and *Consumer* strategies. However, the optimal strategy selection depends on the investor's preferences. A defensive investor might favor the *Minimum Variance Portfolio*, prioritizing stability, while a more risk-tolerant investor may opt for the *Equal Weighted Portfolio*, recognizing the potential for higher returns with increased risk.

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A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

SECTOR-BASED CREDIT RISK AND STOCK RETURNS

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Abstract:

The credit risk-return puzzle challenges traditional asset pricing models. By suggesting that low credit risk outperforms high credit risk securities, it indicates a conflict in investors' perceived risk. This study explores the phenomenon by attributing credit risk-return dynamics in stocks to sectors' economic cycle exposure and examines its potential to uncover investment opportunities. The findings reveal that economic cycles may influence perceived risk. The results show the efficacy of constructing long-short and long-only portfolios based on these insights. While both portfolios outperform the market, the long-short portfolio excels in diversification potential due to its lower volatility and consistent performance.

Keywords: Finance, Quantitative Investments, Financial Markets, US Stock Market,
Credit Risk, Sectors-based.

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1. Introduction

The link between risk and returns is a key dynamic in financial markets. According to the Traditional Asset Pricing models, higher risk should yield higher returns as investors seem to pay a premium for undertaking risk. However, numerous studies that explored the relationship between credit risk and returns, presented evidence supporting an anomalous pattern also known as the credit risk-return puzzle. There is a negative relationship between credit risk and stock returns in which low-credit-risk firms outperform high-credit-risk firms. This implies that investors may not perceive higher credit risk as a significant factor that warrants higher expected returns as the fundamental principles predict.

As the credit risk-return puzzle is a thoroughly researched yet not entirely comprehended phenomenon, the main objective of this study is to build a quantitative investment strategy on sector-based credit risk and stock returns. While numerous studies have delved into the relationship across the entire market, this study distinguishes itself by focusing on a deeper exploration of the credit risk-return relationship within sectors. It investigates why low credit ratings are not perceived as risky by investors in some sectors.

The idea behind the research is that the perception of credit risk varies across sectors due to the different dynamics of each industry. In other words, some sectors are less exposed to economic cycles than others. For instance, sectors that are considered to be defensive, such as utilities, and consumer staples, provide goods and services that are indispensable regardless of the economic conditions. Therefore, in these defensive sectors, even during downturns, the demand will remain relatively constant, leading investors to perceive high-credit risk stocks as less risky due to their economic resilience. A better understanding of these dynamics may provide valuable insights into this phenomenon but can also assist investors in identifying investment opportunities and refining their strategies.

The remainder of the study is organized as follows. Section two is the Literature Review, which is an overview of the most critical findings. Section three is the Data and Methodology, where the data is presented, and the signal and portfolio construction are discussed. Section four corresponds to the performance evaluation of the sectors portfolios, to confirm the influence of sectoral economic cycles. Section five corresponds to the results of the portfolios constructed based on the sectors' analysis considering both in-sample and out-of-sample sector analysis. Finally, the conclusion is presented in section six.

2. Literature Review

Numerous studies have explored the relationship between risk and returns and valuable insights were found in various studies. Sharpe's (1964), and Lintner's (1965) contributions to the financial world laid the foundation for the Capital Asset Pricing Model (CAPM). The model suggests that in an efficient market with equilibrium, higher-risk assets are expected to have higher returns to compensate investors for taking on risk, forming the basis for the risk-return tradeoff. Another notable contribution to this area was made by Fama and French (1993). Their work expands the CAPM, suggesting that expected returns increase with exposure to factors such as size and value, acknowledging a positive relationship between risk and return. Chava and Purnanandam (2009) also find a positive cross-sectional relationship using an ex ante proxy to estimate expected returns, they prove that for investors to bear higher credit risk, higher expected returns are required.

Contrary to the observed positive dynamics between risk and returns in these studies, others not only deepened but also introduced a different perspective, a negative relationship between credit risk and returns. Dichev and Piotroski (2001) demonstrated negative abnormal returns revealing that firms with low credit ratings tend to perform poorly after credit downgrades, often due to market underreaction. Griffin and Lemmon (2002) find a negative relationship between distress risk and stock returns that underperforming firms with elevated credit risk frequently exhibit low book-to-market ratios, indicating possible mispricing. Campbell et al. (2008) contributed to the negative dynamics evidence showing that the impact of distress is more accentuated in small and illiquid stocks. Avramov et al. (2009) showed that the credit risk puzzle is stronger around downgrades of stocks with worse rates.

In conclusion, these studies provide multiple insights into the credit risk-return relationship within the entire market. Yet, by contradicting fundamental models, the gaps in comprehension persist, leaving room for further exploration, particularly when looking into the sector's dimension. This study builds upon these previous discoveries to further contribute to unraveling the complexities of credit risk-return dynamics.

3. Data & Methodology

3.1 Data

The sample contains US companies with monthly returns and S&P Domestic Long-Term Issuer Credit Rating available in Compustat via the Wharton Research Database (WRDS) from May 1987 to February 2017. The lack of access to recent data limits the study's ability to capture more recent market dynamics or economic shifts that have occurred post-2017. The credit rating definition provided by Standard & Poor's before 1998 pertained to the issuer's senior debt rating. However, from 1998 onward, the firm's credit rating is now based on the overall quality of its outstanding debt, whether publicly or privately held. The risk-free rate, together with the other Fama-French Three monthly factors was achieved from the Ken French Website via WRDS.

3.2 Data Curation

Building upon prior research in the field of credit ratings, the alphabetical grades were transformed into standard numerical values. Precisely, a rating of 1 corresponds to AAA, while a rating of 22 signifies a D rating[1]. Therefore, higher numerical values represent a greater level of credit risk. The ratings will serve as signal criteria for the portfolios, where stocks with ratings classified as investment grade, with numerical values of 10 or lower (equivalent to BBB- or better), are distinguished from those stocks categorized as non-investment grade, with values of 11 or higher (equal to BB+ or worse).

3.3 Sectors

In this study, the Global Industry Classification Standard (GICS) was adopted as the framework for sector analysis. GICS is a widely recognized system that categorizes industries into hierarchical levels for a comprehensive assessment. The eleven sectors of GICS' first level and their corresponding codes are as follows: *Energy (10), Materials (15), Industrials (20), Consumer Discretionary (25), Consumer Staples (30), Health Care (35), Financials (40), Information Technology (45), Communication Services (50), Utilities (55), Real Estate (60).*

The sensitivity of a sector to the overall economic fluctuations is measured by its beta. Table 1 presents the beta values for each sector, enhancing comprehension of their respective exposures to these fluctuations. A beta greater than one indicates a higher exposure of the sector to economic cycles, whereas a beta lower than one suggests a comparatively lower exposure.

Table 1: Sectors Betas

	Sector 10	**Sector 15**	**Sector 20**	**Sector 25**	**Sector 30**	**Sector 35**	**Sector 40**	**Sector 45**	**Sector 50**	**Sector 55**	**Sector 60**
Beta	0.997	1.201	1.183	1.267	0.758	0.932	1.004	1.642	1.354	0.373	0.886

Thus, as it is expected, defensive sectors, *such as Consumer Staples (30),* and *Utilities (55),* exhibit the lowest betas of 0.758, and 0.373 respectively, reflecting their stability in providing essential

[1]The complete range of ratings: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22.

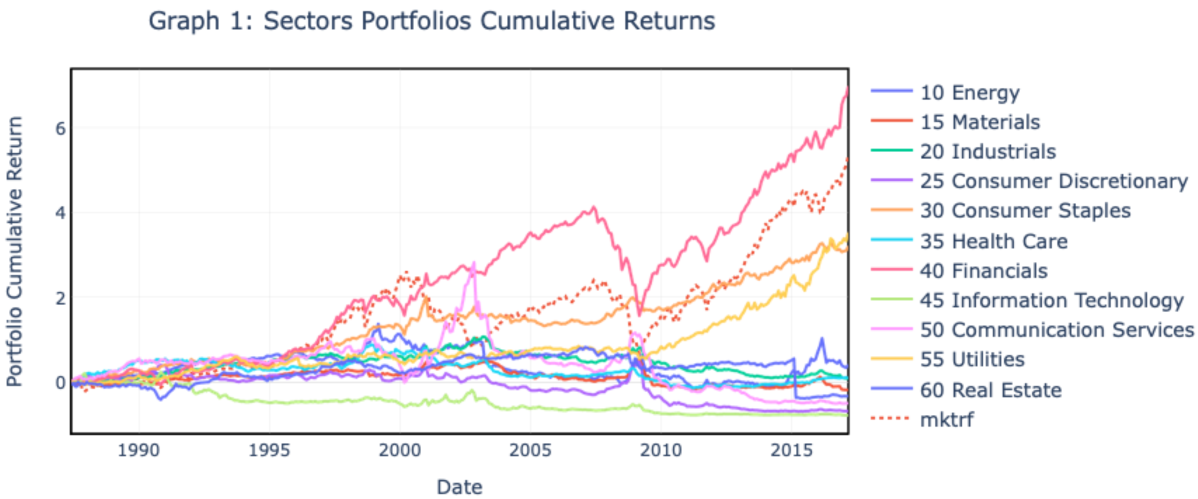
products and services. In contrast, *Information Technology (45)* and *Communication Services (50)* displayed the highest betas of 1.642 and 1.354 respectively.

3.4 Portfolios Construction

To confirm that the sector's exposure to economic cycles influences the credit risk-return relationships of stocks within the sector, long-short strategies were developed for each sector to compare their securities performances. Given the overall expectation that stocks in defensive sectors with higher credit risk will be perceived as less risky, resulting in a more pronounced negative credit risk-return relationship, the portfolios were constructed by taking a long position on investment-grade stocks while shorting non-investment-grade stocks each month. The portfolios are computed on an equal-weighted basis to ensure a fair and unbiased comparison of stock performance. Thus, the expectation is that in defensive sectors better portfolio performances can be achieved.

Subsequently, based on this previous sectoral analysis, a long-short portfolio and a long-only portfolio are formed. The portfolios' composition is determined by the three best-performing sectors each month. This selection is based on the average of the ranks derived from historical data, considering both cumulative returns and the Sharpe ratio. To ensure a robust foundation for sector selection, a minimum of twelve months of historical data requirement is set. Consequently, these new portfolios are set to start in May 1988. This measure ensures that the portfolios are built upon substantial historical data, enhancing the reliability of the monthly selection of the best-performing sectors. The long-short portfolio takes a long position on the investment grade stocks of these best sectors each month and a short position on the non-investment grades of these same sectors. The long-only portfolio consists of only taking a long position on investment-grade stocks within the same identified top three sectors each month.

4. Sectors Performance Evaluation



The cumulative excess returns of all the sectors' portfolios, along with the market risk-free cumulative returns, are presented in Graph 1. It reflects a one-time investment in May 1987 with monthly rebalancing. As it is possible to observe, the *Financials (40)* sector's portfolio was the only one that outperformed the market. However, it is also possible to observe that the *Consumer Staples (30)* sector outperforms the market at different points in time over the full period, particularly during major market downturns. Further insights can be derived when comparing the sectors' portfolios. Most sectors start the observation period with a positive and slightly increasing cumulative return, however, most of them begin to decline at the beginning of the 21st century, leading some to end up with negative cumulative returns. These results indicate that indeed sectors may exhibit unique risk-return dynamics according to their vulnerability to economic cycles.

Thus, the performance metrics were displayed in Table 2 for the full period to further analyze and better understand the sector's portfolios and their credit risk-return dynamics. When analyzing the table, is it possible to observe that, there are notable differences in annual returns, annual volatility, and Sharpe ratios across sectors. It is possible to conclude that the sectors that present the highest annual returns are also the sectors with the highest Sharpe ratios, notably the

Consumer Staples (30), the *Financials (40),* and the *Utilities (55)*. Furthermore, it is possible to observe that these three sectors are the only ones that overperform the benchmark based on the Sharpe ratio, a risk-adjusted performance metric. Conversely, *Consumer Discretionary (25)*, *Information Technology (45)*, and *Communication Services (50*) besides presenting negative Sharpe ratios are also sectors that present the lowest annual returns and higher volatility, heightening the fact that these sectors are very exposed to economic cycles.

Table 2: Performance Metrics

FULL PERIOD							
Sector	**Annual Return**	**Annual Volatility**	**Sharpe Ratio**	**Sector**	**Annual Return**	**Annual Volatility**	**Sharpe Ratio**
10	0.011	0.137	0.082	**40**	0.072	0.109	0.661
15	-0.007	0.087	-0.078	**45**	-0.050	0.168	-0.299
20	0.003	0.071	0.039	**50**	-0.023	0.177	-0.131
25	-0.038	0.138	-0.276	**55**	0.052	0.086	0.602
30	0.049	0.075	0.660	**60**	-0.013	0.149	-0.089
35	0.003	0.079	0.039	**mktrf**	0.064	0.152	0.420

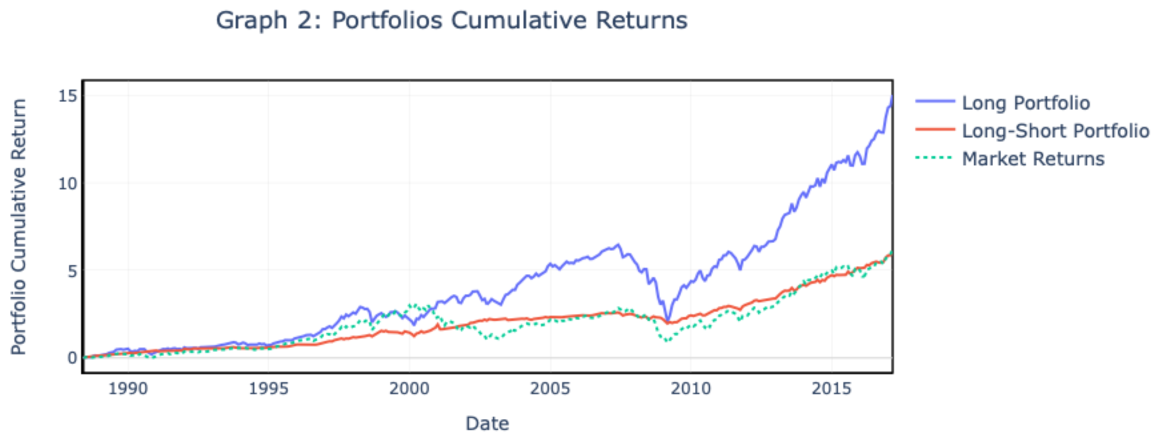
In summary, the results of the sector's portfolios suggest that *Consumer Staples (30)*, *Financials (40)*, and *Utilities (55)* have exhibited the best performances. While the robust performances of *Consumer Staples (30)* and *Utilities (55)* align with expectations given their defensive nature, the remarkable performance of the *Financials (40)* sector was not necessarily anticipated. A plausible explanation for the *Financials (40)* sector's strong performance can also lie in the stability and predictability of the sector. In other words, the sector benefits from a robustly regulated environment, characterized by the implementation of rules, regulations, and monitoring mechanisms by government authorities. This regulatory framework has the potential to cultivate a positive investor sentiment contributing to explaining the observed negative credit risk-return relationship, as investors potentially consider high credit risk as less risky within the stable environment of the sector.

The outperformance of *Consumer Staples (30)* and *Utilities (55)*, confirms the defensive characteristics of these sectors that make high credit risk stocks not risky in the inventor's eyes. Conversely, the sectors with the weakest performances, namely *Consumer Discretionary (25)*, *Information Technology (45)*, and *Communication Services (50*), were in line with expectations. These sectors exhibited the highest betas, suggesting heightened exposure to economic cycles. Consequently, investors in these sectors might perceive high-credit-risk stocks as risky, explaining the underperformance of the portfolio, particularly as high-credit-risk stocks outperformed low-credit-risk stocks. All in all, as the results strongly suggest that the credit risk-return relationship is indeed influenced by sectors' exposure to economic cycles, investment strategies based on this relationship may prove to be great investment opportunities. However, the unexpectedly strong performance of *Financials (40)* highlights the complexity of sector dynamics and the importance of considering multiple factors when evaluating sector performance in the context of credit risk.

5. Results

5.1 Portfolios Performances

The long-short and the long-only portfolios are constructed with the three top-performing sectors each month. In simpler terms, these portfolios are constructed with sectors demonstrating a stronger negative credit risk-return relationship leveraging previous findings. To verify the exploitability of economic cycle exposure in sectors, several key indicators will be examined. Their analysis covers three distinct periods: the full period (May 1988 – February 2017), the first half (May 1988 – September 2002) which consists of the in-sample period, and the second half (September 2002 – February 2017), also known as the out-of-sample. Conducting a segmented analysis of the results for the in-sample and the out-of-sample has multiple advantages such as understanding the robustness of the results under different market conditions and economic cycles.



The cumulative returns of the market and the portfolios are displayed in Graph 2. It is clear to observe that while the long-short portfolio is struggling to overperform the benchmark during the observation period, the long-only portfolio can consistently maintain a substantial level of overperformance. Despite this, it is clear that the long-short portfolio presents a less volatile and more consistent performance when compared to the long portfolio. Thus, it is important to highlight the drastic downturn in the long-only portfolio during the crisis of 2008, contrasting with the long-short portfolio that was able to keep a more stable performance over the same period.

Table 3: Portfolios Performance Metrics

	Long	**Long Short**	**Mkt-rf**
FULL PERIOD			
Annual Return	0.101	0.070	0.071
Annual Volatility	0.144	0.063	0.146
Sharpe Ratio	0.702	1.118	0.484
FIRST HALF			
Annual Return	0.102	0.082	0.051
Annual Volatility	0.141	0.069	0.150
Sharpe Ratio	0.724	1.191	0.338
SECOND HALF			
Annual Return	0.100	0.058	0.091
Annual Volatility	0.147	0.055	0.142
Sharpe Ratio	0.681	1.050	0.643

The performance metrics of the long-short and the long-only portfolios are shown in Table 3 for a better understanding of the strategies. Firstly, when analyzing the table, it is possible to observe that for all three time periods, as the graphical results indicate, the long-only strategy yields the highest positive annualized excess returns, surpassing the long-short strategy that presented lower values. Similarly, the long-only portfolio presented for the full period, the first half, and the second half, more than twice as much volatility as the long-short portfolio as it is not hedging. The results also indicated that for all three scenarios, the Sharpe ratios of the long-short portfolio have achieved a superior risk-adjusted return when compared to the long-only portfolio, however, both portfolios were able to overperform the market based on the Sharpe ratio in all three circumstances. All things considered, both portfolios present consistent results between the full period, the in-sample, and the out-of-sample analysis.

5.2 CAPM regression

The regression analysis for the Capital Asset Pricing Model (CAPM) for the full period, first half, and second half is shown in Table 4. According to the CAPM, there are two types of risk. The first risk is the unsystematic, a risk that is specific to the business, and has the potential to be mitigated or eliminated with diversification. The second risk corresponds to the systematic risk, which affects the entire market and is represented by beta.

Table 4: CAPM Regression

	FULL PERIOD		FIRST HALF		SECOND HALF	
	Long	**Long Short**	**Long**	**Long Short**	**Long**	**Long Short**
Alpha	0.004	0.005	0.005	0.006	0.001	0.003
	(2.765)	(5.176)	(2.595)	(4.187)	(0.900)	(2.937)
Beta	0.811	0.176	0.703	0.114	0.934	0.248
	(26.876)	(8.339)	(14.798)	(3.333)	(27.134)	(10.790)
IR	0.086	0.257	0.132	0.311	0.030	0.176

* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

Alpha is the regression intercept in the CAPM equation that represents the excess return of the investment beyond what would be predicted by its beta. Thus, a positive alpha indicates that the investment strategy has outperformed market expectations indicating potential strengths or competitive advantages. It is possible to observe that for the full period, both portfolios present a positive alpha that is statistically different from zero demonstrating an outperformance relative to the systematic risk. The regressions presented significant beta values, revealing a higher correlation of the long-only portfolio to the market than the long-short. The information ratio (IR) measures the risk-adjusted returns of the strategies beyond the return of a benchmark. Therefore, as both portfolios presented positive IR over the full period, it indicates an effective performance. These results suggest that the portfolios consistently outperform during the full period, and both portfolios offer superior risk-adjusted returns than the benchmark's, highlighting their potential for delivering favorable investment outcomes even when accounting for varying levels of market risk.

When comparing the first half to the full period, no notable discrepancies emerge. In other words, both alphas and betas are significant and positive and were able to keep positive its risk-adjusted returns beyond the benchmark. On the other hand, when it comes to the second half, there is one main difference. The long-only portfolio alpha is non-significant at a 5% significance level, making only the long-short strategies outperform what was anticipated given their systematic risk. The betas and the information ratios, despite some variations in their values, remain positive. The consistent performance of the model across both in-sample and out-of-sample datasets suggests its robustness, indicating its ability to navigate various market conditions effectively.

5.2 FF3 regression

The Fama-French Three Factor Model (FF3) in Table 5 enhances the CAPM by introducing two critical factors—'Small Minus Big' (SMB) and 'High Minus Low' (HML). These factors encapsulate historical trends, revealing the superior performance of smaller and value stocks compared to larger and growth stocks.

Table 5: FF3 Regression

	FULL PERIOD		FIRST HALF		SECOND HALF	
	Long	**Long Short**	**Long**	**Long Short**	**Long**	**Long Short**
Alpha	0.002	0.004	0.002	0.005	0.002	0.003
	(1.960)	(5.519)	(1.211)	(4.416)	(1.372)	(3.196)
Mkt-Rf	0.888	0.235	0.923	0.198	0.861	0.267
	(38.383)	(13.128)	(23.236)	(6.649)	(28.163)	(11.048)
SMB	-0.071	-0.235	-0.077	-0.267	0.013	-0.159
	(-2.269)	(-9.692)	(-1.745)	(-8.068)	(0.251)	(-3.752)
HML	0.524	0.158	0.574	0.139	0.465	0.092
	(15.601)	(6.083)	(10.045)	(3.249)	(9.753)	(2.436)
IR	0.045	0.226	0.046	0.257	0.037	0.183

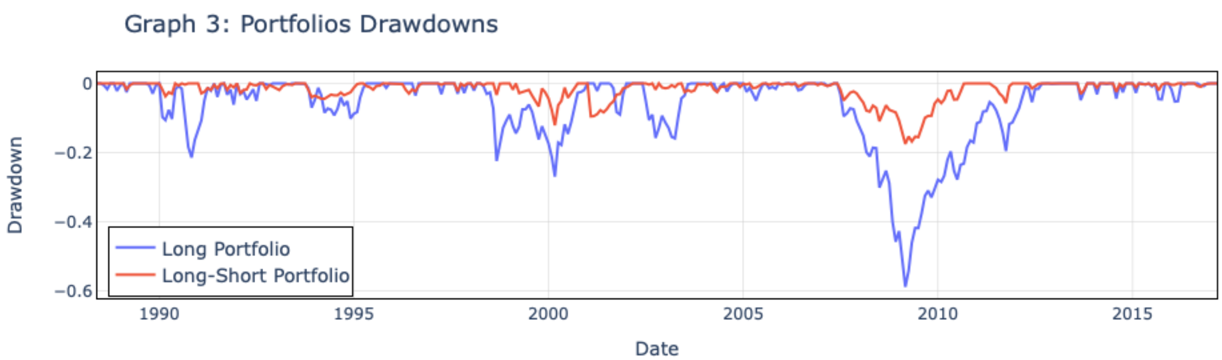
* The t-statistics are in parenthesis ** Analysis done for a 5% significance level

When comparing the FF3 regression to the CAPM regression results, it is possible to observe for the full period, as before, the long-only and the long-short portfolios displayed significant and positive alpha values. In addition, they also have significant positive Mkt-Rf betas, of 0.888 for the long portfolio and 0.235 for the long-short portfolio. The SMB is negative and statistically significant for both portfolios suggesting that, on average, the strategies tend to underperform when investing in smaller stocks compared to larger stocks. Conversely, the HML is positive and significant for both, suggesting that value stocks outperform growth stocks. The two portfolios also presented positive information ratios, indicating excess returns on a risk-adjusted basis when compared to the benchmark.

While the long-short portfolio, presented similar results under all three scenarios, with no relevant changes, significant variations emerge when analyzing the performance of the long portfolio during the first and second halves. Although the in-sample and out-of-sample results demonstrate notable similarity, they deviate from the results of the full-period analysis. The main distinctions lie in the long-only alpha and SMB components. The alphas of the long-only portfolio are not significant, implying that there is no evidence of excess returns that cannot be explained by the factors of the Fama-French Three Factor Model. In addition, during these periods the SMB are non-significant, indicating that the strategy does not seem to be influenced significantly by movements in the returns of small-cap stocks relative to large-cap stocks.

Thus, the regression analyses highlight an important distinction between the portfolios. While the long portfolio results from both the in-sample and out-of-sample analyses deviated from the findings of the full-period sample, the long-short portfolio exhibited remarkable consistency between all three scenarios, implying greater robustness and reliability in the performance.

5.4 Drawdowns



To better understand the risk of the portfolios, the drawdowns are displayed in Graph 3. It shows the peak-to-trough decline of the portfolios and, therefore, is an essential tool to indicate the magnitude of potential losses the investment may experience. The results confirm the previous analysis, suggesting that the long-short strategy demonstrates greater stability and consistency than the long-only strategy since it suffers less significant and less frequent peaks. Both strategies have their main peaks at the same moment in time, however, the long-only portfolio presents a maximum drawdown of -58.89%, which surpasses more than triple the maximum drawdown of the long-short portfolio of -17.51%. Thus, it shows that the long-only portfolio offers a greater downside risk than the long-short portfolio.

6. Conclusion

Sectors characterized with lower exposure to economic cycles indeed exhibited stronger negative dynamics between credit risk and returns. This means that in these sectors, high-credit-risk stocks are deemed by investors as not risky resulting in low-credit-risk outperforming high-credit-risk firms. In contrast, sectors with high vulnerability to business cycles presented worse performance suggesting a weaker negative credit risk-return relationship as a result of high-credit-risk firms outperforming low-credit-risk firms. Therefore, these findings support the theory of the credit risk-return relationship being influenced by the sector's exposure to economic cycles, indicating its potential to assist investors in identifying investment opportunities. However, as previously mentioned, this topic of study still presents gaps, and additional research is necessary, particularly considering various factors within sectors that may influence the negative dynamics, as observed in the financial sector.

All in all, the analysis suggests that, when forming portfolios with sectors with negative risk-return dynamics, the long-only strategy outperforms in terms of returns. However, the long-short strategy emerges as a viable approach for mitigating risk and enhancing portfolio stability. This portfolio also delivers more consistent results over time as it could be observed with the in-sample and out-of-sample analysis. Moreover, given that the long-short strategy also exhibits lower volatility with reduced maximum drawdown, it can be deemed more fitting to offer enhanced diversification benefits. However, as the strategies require investments in multiple stocks, there is potential for increased transaction costs. Hence, investors' preferences and goals such as risk tolerance, investment objectives, and time horizon play a crucial role in determining the most suitable approach to invest in.

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