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

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Abstract

The study delves into the performance of the MRTS 452 – General Merchandise Stores signal across 32 years, linking it to the 12 Industry Portfolios from Fama-French. In contrast to findings in smaller time frames, the signal did not replicate similar risk-adjusted performance for the Consumer Discretionary/Durable sector. However, the combination of the 12 sectors into a Long-Short strategy emerged as a resilient approach, exhibiting heightened diversification, effective risk mitigation, and adaptability to varying market conditions. This strategy excelled in managing downside risk, challenging the efficient hypothesis. Concurrently, the Long-Only portfolio demonstrated superior overall returns and lower volatility, outperforming the benchmark.

Keywords: Consumer Behavior; Consumer Spending; Quantitative Strategies; Market Signals

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1 Introduction

Consumer spending plays a pivotal role in propelling economic growth and serves as a vital indicator of overall economic well-being. Constituting nearly 70% of the United States' gross domestic product (GDP), spending behavior wields substantial influence. The exploration of the intricate interplay between consumer spending and stock market sectors seeks to uncover discernible patterns and their potential implications for investors.

As individuals engage in purchasing goods and services, businesses thrive, fostering increased revenue, job opportunities, and overarching economic expansion. Consequently, fluctuations in consumer spending reverberate across various sectors and industries. The behaviors of consumers hinge on diverse factors, encompassing income levels, employment statistics, inflation, interest rates, and overall economic sentiment. During periods of robust growth, heightened consumer confidence may drive increased spending, potentially contributing to a bullish stock market. Conversely, economic downturns might prompt consumers to curtail expenditures, resulting in reduced spending and a bearish market outlook.

Several noteworthy studies have delved into consumer behavior and its implications for the broader market. Gupta, Leung, and Roscovan's (2022) research employs a proprietary dataset containing detailed transaction-level information for a selection of U.S. consumer-focused stocks, investigating the correlation between credit/debit card spending and future stock returns. A long-short strategy demonstrates substantial 16% net annual returns, implying that transaction-level data from consumer activities can effectively indicate a company's forthcoming growth. Additionally, Huang (2018) highlights that positive customer product ratings are predictive of a firm's revenue, establishing a connection between consumer sentiments and stock prices.

Section 2 details the data and methodology, section 3 explores empirical results, assessing sectorial impact, and a Long-Short portfolio strategy, concluding in section 4.

2 Data and Methodology

The Monthly Retail Trade Survey (MRTS) is a crucial economic survey conducted by the United States Census Bureau, designed to capture, and disseminate timely data on retail and food service sales. This data is fundamental for evaluating the health and performance of the retail sector, a key component of the broader economy. Understanding consumer spending patterns, as revealed by the MRTS, is particularly significant given that resultant cash flows from sales play a measurable role in shaping economic landscapes.

The MRTS covers a diverse range of establishments and businesses engaged in retail trade, collecting information from a nationwide sample every month. The results of the survey are published with a lag of 1.5 months, providing a comprehensive and detailed overview of retail sales performance. Additionally, there is the Advance Monthly Retail Trade Survey (MARTS), released two weeks after the end of each month. While MARTS offers more immediate insights, its historical data undergoes corrections to align more closely with the MRTS figures, making it unsuitable for rigorous backtesting.

The focus of the analysis involves a specific signal, the General Merchandise Stores (coded as 452), due to its sensitivity to changes in consumer behavior. As the paper by Gupta, Leung, and Roscovan (2022) points out, the private dataset used between 2013 and 2019 had a 90% correlation with this metric.

The economic motivation behind analyzing consumer spending through the MRTS lies in its potential to offer early signals of future stock prices. With consumer spending playing a substantial role in GDP, understanding trends in this area can provide insights into economic conditions and potential market movements. Information is particularly valuable for short-term decision-making, given the market's sensitivity to news and events. In a flourishing economy, consumers tend to increase spending on non-essential items, positively impacting the sales and profitability of such stores. Conversely, economic downturns or periods of uncertainty may lead to reduced spending on discretionary goods, affecting the performance of these stores.

To understand the impact of the Survey (MRTS) in various industries, the study utilizes the 12 Industry portfolios from the Kenneth R. French Library. These sectors in these portfolios are constructed using a value-weighted approach for all listed tickers on the three major American exchanges, with rebalancing occurring every June. Each return is reported in excess, indicating that the risk-free rate has already been deducted from the calculations. The 12 Industries and the business domains associated with each sector are delineated as follows:

Table 1 - Industry Sectors

Sector	Industry
NoDur	Food, Tobacco, Textiles, Apparel, Leather, Toys
Durbl	Cars, TVs, Furniture, Household Appliances
Manuf	Machinery, Trucks, Planes, Office Furniture, Paper, Computer Printing
Enrgy	Oil, Gas, and Coal Extraction and Products
Chems	Chemicals and Allied Products
BusEq	Computers, Software, and Electronic Equipment
Telcm	Telephone and Television Transmission
Utils	Utilities
Shops	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
Hlth	Healthcare, Medical Equipment, and Drugs
Money	Finance
Other	Mines, Construction, Building Materials, Transportation, Hotels, etc.

Given that both the signal and the returns dataset span the period from 1992 to 2023, segmentation was introduced specifically before the pivotal year of 2008 to evaluate performance across two distinct timeframes, an approach that allows for the assessment of the MRTS signal in moments of crisis. The expectation is that consumers will alter their consumption levels during times of stress, to increase savings and the behavioral shift could act as an early signal to the markets.

Additionally, the study constructs a *Long-Short* portfolio using equal weights for all 12 sectors. When the sales of 452 – General Merchandise Stores are positive, the portfolio takes a long position in all sectors. Conversely, when sales are negative, indicating a decline, the portfolio takes a short position. The transition from long to short happens only when the signal shifts mid-month. This portfolio differs from the approach used by Gupta, Leung, and Roscovan

(2022), who focused specifically on *Improving Minus Worsening* individual stocks of the Consumer Discretionary sector (equivalent to the paper's *Durables* sector). Instead, the focus here is on capturing the overall general trend in all economic sectors. For the sake of simplicity, this study does not account for any transaction costs.

A comparative analysis aims to assess the power of the 452 – General Merchandise Stores signal in providing a reliable source of returns for all sectors. By employing a *Long-Short* portfolio based on the MRTS data, the study seeks to demonstrate the effectiveness of capturing trends and generating returns across diverse industries, and how it compares to a Long-Only and Market portfolio.

The analysis delves into the Capital Asset Pricing Model (CAPM) and the Fama-French Three-Factor Model (FF3), employing statistical tests and measures to assess the robustness of the obtained results. The calculated alpha and beta coefficients, along with their corresponding t-statistics, play a crucial role in validating the model. For the CAPM, the alpha provides insights into the risk-adjusted excess returns, while the beta signifies the sensitivity of the portfolio returns to market movements. Similarly, in the FF3 model, betas are computed for market, size (SMB), and value (HML) factors, capturing additional dimensions of risk. The t-statistics associated with these parameters offer a measure of their statistical significance, helping to evaluate whether the estimated coefficients are reliably different from zero, contributing to the overall credibility and reliability of the findings, and enhancing confidence in the model outcomes and their interpretation.

In summary, the Monthly Retail Trade Survey (MRTS) could prove to be instrumental in gauging consumer spending patterns and influencing the market sector as part of a well-diversified *Long-Short* portfolio.

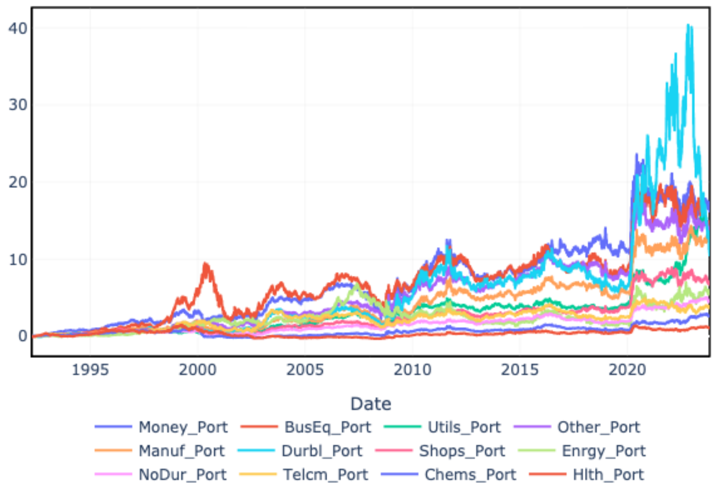
3. Empirical Results

3.1 Empirical Results Per Sector

Table 2 - Full Period Sectorial Performance

Sector	Return	Volatility	Sharpe Ratio	Max Return	Min Return	VaR	Cum. Ret.	Drawdown	Positive Days
NoDur	6.57%	14.88%	0.441	54.46%	-13.44%	-2.49%	459%	-34.75%	50.96%
Durbl	11.69%	27.96%	0.418	232.40%	-69.51%	-5.03%	1065%	-72.21%	51.16%
Manuf	10.35%	20.83%	0.497	87.95%	-30.15%	-3.56%	1219%	-49.51%	51.32%
Enrgy	9.44%	26.54%	0.356	106.52%	-35.93%	-4.27%	546%	-70.50%	50.68%
Chems	5.67%	17.68%	0.32	44.55%	-46.13%	-2.84%	264%	-64.60%	50.43%
BusEq	11.94%	25.95%	0.46	139.69%	-25.07%	-4.41%	1394%	-71.61%	51.36%
Telcm	7.03%	20.12%	0.35	59.41%	-30.89%	-3.40%	384%	-51.00%	50.84%
Utils	10.09%	17.44%	0.579	64.61%	-20.22%	-2.77%	1389%	-38.53%	51.91%
Shops	8.39%	18.85%	0.445	74.10%	-46.75%	-3.23%	703%	-63.05%	51.41%
Hlth	3.95%	18.26%	0.216	51.35%	-32.74%	-3.08%	105%	-72.90%	50.86%
Money	12.14%	24.70%	0.492	60.79%	-25.00%	-4.25%	1662%	-58.67%	51.54%
Other	10.47%	19.91%	0.526	74.95%	-18.81%	-3.43%	1353%	-38.29%	51.26%
Market	8.81%	18.52%	0.475	35.12%	-37.64%	-3.31%	834%	-59.28%	53.61%

Graph 1 – Cumulative Returns of the 12 Industries



In the 32 years, the difference in sectoral performance is notable, according to Table 2, the *Utilities*, *Other*, *Manufacturing*, and *Money* sectors had superior risk-adjusted performance, compared to the Market. This is mainly due to the respective returns beating the benchmarks, but also in the case of *Utilities*, having a lower volatility. One thing in common among all the sectors was their maximum annual return was higher than what was achieved by the market, as 2020 turned out to be the "Best Year" for 8 out of the 12 sectors. This behavior was almost replicated when measuring the minimum annual return, where only the *Durables*, *Chemicals,* and *Shops* sectors dropped higher than the market.

The amazing performance of the *Utilities* sector also transpires to the Value at Risk (VaR) and the maximum drawdown; the sector was among the lowest in both metrics, thus cumulative returns were paramount but inferior to the *Business Equipment* and *Money* sectors.

Conversely, the *Durables* sector's performance has fallen short of expectations. Gupta, Leung, and Roscovan (2022) research proposes a strong correlation between consumer spending and discretionary sales. Despite its high returns, the sector exhibited extreme volatility, leading to a modest Sharpe Ratio. Although it recorded an impressive maximum annual return of 232.4% in 2020, just three years later, the sector faces a substantial decline of approximately 70%, elevating its Value at Risk to the highest among all sectors. The *Durables* all-time high of 4038% has been met with a significant drawdown of -72%.

In the end, the MRTS signal was able to generate positive returns above 50% for all the sectors in the last 32 years.

Table 3 - Full Period Regression

	CAPM			*FF3*				
Sector	**Info Ratio**	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
NoDur	0.028	0.026*	0.003	0.028	0.027*	0.002	-0.009	-0.069*
Durbl	0.025	0.045*	0.043*	0.027	0.047*	0.033	0.135*	-0.213*
Manuf	0.031	0.04*	0.026*	0.032	0.041*	0.02	0.056*	-0.134*
Enrgy	0.024	0.041*	-0.088*	0.024	0.04*	-0.092*	0.129*	0.008
Chems	0.020	0.023	-0.006	0.021	0.024	-0.009	0.016	-0.1*
BusEq	0.026	0.042*	0.158*	0.028	0.046*	0.145*	0.068*	-0.455*
Telcm	0.021	0.027	0.033*	0.022	0.028*	0.028*	0.043	-0.164*
Utils	0.038	0.042*	-0.049*	0.038	0.042*	-0.05*	0.009	-0.001
Shops	0.027	0.031*	0.051*	0.028	0.033*	0.045*	0.04	-0.193*
Hlth	0.013	0.014	0.037*	0.014	0.016	0.031*	0.018	-0.209*
Money	0.031	0.048*	0.008	0.032	0.049*	0.004	0.027	-0.124*
Other	0.032	0.041*	0.026*	0.034	0.042*	0.02	0.075*	-0.166*

*t-statistics is significant ** Analysis done for a 5% significance level

Under the CAPM model the noteworthy performance of the *Utilities* sector becomes apparent, with the highest Information Ratio, with an equally high alpha, although it has a negative exposure to the Market beta, meaning it tends to move in the opposite direction of the overall benchmark. For the FF3 model, the sector retains the same characteristics but its exposure to the SMB and HML factors isn't significant.

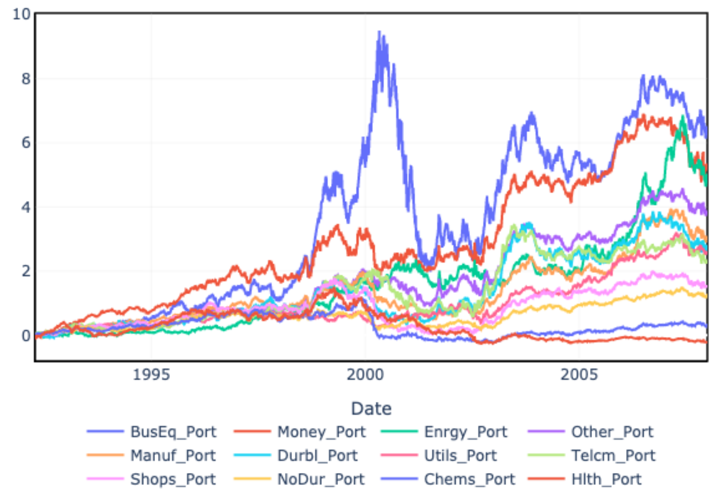
In the *Durables* sector, its alpha stands as the second highest in both models. Under the CAPM, the positive exposure to the beta indicates a tendency to move in sync with the overall market. Similarly, in the FF3 model, a positive exposure to the SMB factor, suggests a preference for returns from small companies. The sector's negative exposure to the HML implies a distinct inclination toward growth stocks over value stocks.

3.1.1 Empirical Results Per Sector First Period

Table 4 - First Period Sectorial Performance

Sector	Return	Volatility	Sharpe Ratio	Max Return	Min Return	VaR	Cum. Ret.	Drawdown	Positive Days
NoDur	5.83%	13.28%	0.439	43.26%	-9.64%	-2.31%	118%	-34.75%	51.14%
Durbl	10.30%	19.95%	0.516	66.91%	-38.80%	-3.26%	269%	-53.67%	51.54%
Manuf	10.19%	16.51%	0.617	56.35%	-30.15%	-2.88%	300%	-49.51%	51.36%
Enrgy	13.43%	20.41%	0.658	52.68%	-11.03%	-3.24%	495%	-28.35%	51.16%
Chems	2.95%	16.01%	0.184	31.26%	-46.13%	-2.68%	30%	-64.60%	50.73%
BusEq	16.61%	28.11%	0.591	139.69%	-24.78%	-4.69%	632%	-71.61%	52.95%
Telcm	9.45%	19.39%	0.487	59.41%	-30.89%	-3.29%	229%	-48.75%	51.14%
Utils	9.15%	14.72%	0.621	42.61%	-16.91%	-2.62%	255%	-30.83%	51.94%
Shops	7.44%	17.98%	0.414	58.52%	-46.75%	-3.06%	150%	-63.05%	51.82%
Hlth	0.07%	18.27%	0.004	51.35%	-32.74%	-3.26%	-22%	-70.51%	50.76%
Money	13.30%	18.36%	0.725	53.79%	-18.85%	-3.11%	520%	-36.60%	52.63%
Other	11.41%	16.92%	0.674	56.82%	-17.30%	-2.79%	380%	-38.29%	51.49%
Market	7.63%	15.89%	0.48	30.38%	-22.45%	-2.67%	172%	-54.21%	53.43%

Graph 2 – First Period cumulative Returns of the 12 Industries



During the first period analyzed from April 14, 1992, to December 31, 2007, a division into two segments helps illuminate the impact of significant market crises in the first 16 years: the dotcom burst, and the pre 2008 financial crisis. According to Table 4, the *Health*, *Chemicals*, *Shops*, and *Non-Durables* sectors exhibited subpar risk-adjusted performance compared to the Market, being the only sectors failing to surpass benchmark annual returns.

In this pre-financial crisis era, the *Money* sector excelled with the highest Sharpe ratio, driven by the third-highest annual returns, albeit with higher volatility than the market. Notably, 2003 stood out as the "Best Year" for 9 out of the 12 sectors, where all achieved maximum annual returns exceeding the market. Only five sectors had better minimum annual returns, including the *Money* sector. Its robust performance translated into the second-largest cumulative return of 520%, accompanied by a minimal -36.6% maximum drawdown.

Except for the *Non-Durables* and *Utilities*, the Value at Risk (VaR) was higher than the benchmark for everyone. The *Durables* sector's performance was modest, it had high returns, but extreme volatility, leading to a modest Sharpe Ratio, albeit higher than the market. Its maximum annual return was second to *Business Equipment*, a value expected due to the dotcom boom, and its cumulative returns and drawdown results were better than the market.

The MRTS signal provided positive returns for all sectors, although it is apparent that the signal couldn't successfully hedge against the extreme growth in the *Business Equipment* segment, one which encompasses the biggest technology firms, as pre-dotcom crisis the returns for the sector peaked at almost 950%.

Table 5 - First Period Regression

	CAPM			*FF3*				
Sector	**Info Ratio**	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
NoDur	0.021	0	0.002*	0.021	0	0.002*	-0.001*	0
Durbl	0.026	0	0.003*	0.026	0	0.003*	0	0
Manuf	0.030	0*	0.003*	0.034	0*	0.003*	0	-0.001*
Enrgy	0.038	0*	0.002*	0.034	0*	0.002*	0	0.002*
Chems	0.005	0	0.002*	0.005	0	0.002*	0	0
BusEq	0.027	0	0.006*	0.041	0.001*	0.004*	0	-0.008*
Telcm	0.021	0	0.004*	0.028	0	0.003*	-0.001*	-0.002*
Utils	0.036	0*	0.001*	0.030	0	0.002*	0	0.002*
Shops	0.018	0	0.003*	0.022	0	0.003*	0	-0.002*
Hlth	-0.007	0	0.003*	-0.001	0	0.002*	-0.001*	-0.002*
Money	0.037	0*	0.003*	0.039	0*	0.003*	-0.001*	-0.001
Other	0.034	0*	0.003*	0.039	0*	0.002*	0	-0.002*

*t-statistics is significant ** Analysis done for a 5% significance level

Under the CAPM model the noteworthy performance of the *Money* sector becomes apparent, with one of the highest Information Ratio, beaten by the *Energy* sector. All alphas in the sample were extremely small, with only 5 sectors having statistical significance. The exposure to the market, measured through beta, was positive and significant for all, in both models. The *Money* sector did have a negative exposure to the SMB factor, under FF3, revealing a preference for returns of big companies, which could include the biggest banks and other financial intermediaries, but its negative exposure to HML factors isn't significant.

In the *Durables* sector, for both models, significance was only found in the market beta, indicating a positive tendency to move in the same general direction.

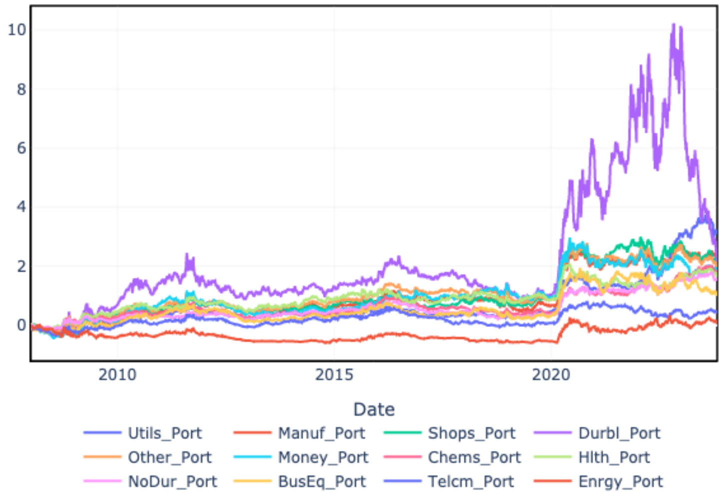
3.1.2 Empirical Results Per Sector Second Period

Table 6 - Second Period Sectorial Performance

Sector	Return	Volatility	Sharpe Ratio	Max Return	Min Return	VaR	Cum. Ret.	Drawdown	Positive Days
NoDur	7.30%	16.31%	0.447	54.46%	-13.44%	-2.58%	157%	-33.75%	50.78%
Durbl	13.07%	34.11%	0.383	232.40%	-69.51%	-6.07%	216%	-72.21%	50.78%
Manuf	10.50%	24.38%	0.431	87.95%	-14.04%	-3.97%	230%	-34.38%	51.28%
Enrgy	5.47%	31.48%	0.174	106.52%	-35.93%	-4.94%	9%	-61.29%	50.20%
Chems	8.37%	19.20%	0.436	44.55%	-16.63%	-3.03%	181%	-33.15%	50.13%
BusEq	7.30%	23.61%	0.309	93.60%	-25.07%	-4.04%	104%	-36.71%	49.77%
Telcm	4.62%	20.81%	0.222	55.15%	-24.57%	-3.59%	47%	-40.37%	50.55%
Utils	11.02%	19.77%	0.558	64.61%	-20.22%	-3.14%	320%	-29.36%	51.88%
Shops	9.33%	19.68%	0.474	74.10%	-15.88%	-3.49%	222%	-29.80%	51.00%
Hlth	7.80%	18.25%	0.427	42.53%	-15.46%	-2.92%	164%	-31.53%	50.95%
Money	10.99%	29.68%	0.37	60.79%	-25.00%	-5.13%	184%	-47.69%	50.45%
Other	9.53%	22.49%	0.424	74.95%	-18.81%	-3.87%	203%	-34.12%	51.03%
Market	9.98%	20.82%	0.479	35.12%	-37.64%	-3.94%	244%	-52.00%	53.79%

The second period analyzed from January 1, 2008, to October 31, 2023, was marked by two great events, the 2008 financial and 2020 COVID crisis. Despite this, the US stock market experienced the longest bull run of 11 years between these two events.

Graph 3 – Second Period cumulative Returns of the 12 Industries



The great market performance is then evident, as only the *Utilities* sector outperformed it in terms of risk-adjusted performance, measured by the Sharpe Ratio. According to Table 6, the sector excelled driven by the second-highest annual returns, and lower volatility, both measuring better than the market. As stated previously, 2020 stood out as the "Best Year" for 11 out of the 12 sectors, only *Utilities* generating its highest returns in 2022. The robust performance of the sector translated into the highest cumulative return of 320%, accompanied by a minimal -29.36% in the maximum drawdown.

The *Durables* sector's performance was extreme, it had the highest one-year annual returns of 232.4% in 2020, but the highest volatility in the entire sample at 34%. Since then, the returns of the sector have vanished in 2023, this sector has dropped almost 70% in one year, with the maximum drawdown registering -72.21%. Intriguing is the cumulative returns peaked at 1021.91%, meaning that a similar signal, as used by Gupta, Leung, and Roscovan (2022), can't generate sustained returns in the same period.

Table 7 - Second Period Regression

	CAPM			*FF3*				
Sector	**Info Ratio**	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
NoDur	0.032	0*	-0.001*	0.033	0*	-0.001*	0.001*	0
Durbl	0.026	0.001	-0.001*	0.025	0.001	-0.001*	0.003*	-0.002*
Manuf	0.031	0	-0.001*	0.031	0*	-0.002*	0.002*	0
Enrgy	0.016	0	-0.002*	0.017	0	-0.003*	0.003*	0.001*
Chems	0.032	0*	-0.001*	0.032	0*	-0.001*	0.002*	0
BusEq	0.022	0	-0.001*	0.021	0	-0.001*	0.002*	-0.002*
Telcm	0.019	0	-0.002*	0.019	0	-0.002*	0.003*	0
Utils	0.040	0*	-0.001*	0.040	0*	-0.002*	0.001*	0
Shops	0.033	0*	-0.001*	0.033	0*	-0.001*	0.002*	-0.001*
Hlth	0.031	0	-0.001*	0.030	0	-0.001*	0.002*	-0.001*
Money	0.027	0.001	-0.002*	0.028	0.001	-0.002*	0.003*	0
Other	0.030	0	-0.001*	0.031	0	-0.001*	0.002*	0

*t-statistics is significant ** Analysis done for a 5% significance level

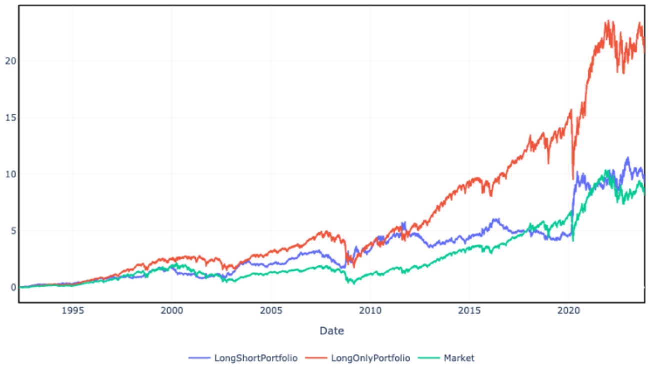
The *Utilities* sector performance under the CAPM model becomes apparent, with the highest Information Ratio. Just 4 alphas in the sample were statistically significant but extremely small. In general, the signal in this period wasn't moving in the same direction as the market, the exposure, measured through beta, was negative and significant for all, in both models. Every sector had a positive exposure to the SMB factor revealing a preference for returns of small companies. In the *Durables* sector, for the FF3 model, significance was also found in the HML factor, it had a negative exposure to this factor.

3.2 Empirical Results Per Portfolio

Table 8 - Full Period Portfolio Performance

Portfolio	**Return**	**Volatility**	**Sharpe Ratio**	**Max Return**	**Min Return**	**VaR**	**Cum. Ret.**	**Drawdown**	**Positive Days**
Long-Short	8.98%	17.51%	0.513	80.05%	-19.00%	-3.06%	946%	-37.77%	51.47%
Long-Only	11.35%	17.50%	0.649	34.25%	-35.53%	-3.11%	2106%	-53.97%	54.61%
Market	8.81%	18.52%	0.475	35.12%	-37.64%	-3.31%	834%	-59.28%	53.61%

Graph 4 – Cumulative Returns of the Portfolios



With the incorporation of both *Long-Only* and *Long-Short* portfolios, we aim to merge the strengths of individual sectors into a unified approach that not only diversifies risk but also outperforms across key metrics. As indicated in Table 8 over 32 years, both portfolios consistently achieved annual returns surpassing those of the Market, while maintaining lower volatility, resulting in elevated Sharpe Ratios. Notably, the *Long-Short* portfolio exhibited remarkable peak performance, reaching a maximum return of 80.05% in 2020, outshining both the *Long-Only* and Market portfolios, which attained their peaks in 2013 with comparatively lower percentage returns.

The *Long-Short* portfolio demonstrated a notably lower value at risk (VaR), signifying a reduced likelihood of extreme negative returns. This is evident in two crucial aspects: a lower minimum annual return and a shallower Drawdown at -37.77%. Both the *Long-Short* and *Long-Only* portfolios consistently outperformed the Market in cumulative returns, showcasing positive returns for over 50% of the observed days.

Table 9 - Full Period Portfolio Regression

	CAPM			*FF3*				
Portfolio	**Info Ratio**	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
Long-Short	0.032	0*	0	0.033	0*	0	0.001*	-0.002*
Long-Only	0.011	0*	0.009*	0.010	0*	0.009*	0*	0.002*

*t-statistics is significant ** Analysis done for a 5% significance level

The *Long-Short* portfolio exhibits a substantially higher Information Ratio in both the CAPM and the FF3 Model in comparison to the *Long-Only*. While the portfolio's alpha is statistically significant, its magnitude is remarkably small. In the regression analyses, the *Long-Short* strategy does not demonstrate a significant Market Beta. However, it shows a positive exposure to the SMB factor, a preference for returns of small companies, and a negative exposure to the HML factor, favoring value stocks over growth stocks.

3.2.1 Empirical Results Per Portfolio First Period

Table 10 - First Period Portfolio Performance

Portfolio	Return	Volatility	Sharpe Ratio	Max Return	Min Return	VaR	Cum. Ret.	Drawdown	Positive Days
Long-Short	9.18%	14.14%	0.649	46.37%	-19.00%	-2.43%	261%	-36.68%	51.94%
Long-Only	12.07%	14.13%	0.854	34.15%	-16.94%	-2.39%	469%	-34.15%	54.75%
Market	7.63%	15.89%	0.48	30.38%	-22.45%	-2.67%	172%	-54.21%	53.43%

Graph 5 – First Period cumulative Returns of the Portfolios

Table 10 provides an in-depth examination of the *Long-Short*, *Long-Only*, and the broader Market portfolio during the initial period spanning from April 14, 1992, to December 31, 2007. Throughout this duration, both the *Long-Short* and *Long-Only* portfolios consistently outperformed the Market, delivering superior annual returns while maintaining lower volatility, resulting in great Sharpe Ratios. Interestingly, the *Long-Short* portfolio showcased a peak return of 46.37% in 2003, outshining the *Long-Only* and Market portfolios, which reached their peaks in 1995 with similar magnitudes.

While the *Long-Only* portfolio demonstrated a reduced Value at Risk (VaR), as indicated by a lower minimum annual return, diminished volatility, and a Drawdown of -34.15%, the *Long-Short* portfolio displayed a comparable performance. Both portfolios consistently exceeded the Market in cumulative returns.

Table 11 - First Period Portfolio Regression

	CAPM			*FF3*				
Portfolio	**Info Ratio**	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
Long-Short	0.031	0*	0.003*	0.036	0*	0.003*	0	-0.001*
Long-Only	0.025	0*	0.009*	0.016	0*	0.009*	-0.001*	0.002*

*t-statistics is significant ** Analysis done for a 5% significance level

The *Long-Short* approach displays an elevated Information Ratio in both the CAPM and the FF3 Model when contrasted with the *Long-Only*. Although the portfolio's alpha is statistically significant, its scale is notably modest. In the regression analyses, the *Long-Short* portfolio reveals a meaningful positive Market Beta. However, it lacks a positive association with the SMB factor and exhibits a negative connection with the HML factor, suggesting an inclination toward growth-oriented stocks.

3.2.2 Empirical Results Per Portfolio Second Period

Table 12 - Second Period Portfolio Performance

Portfolio	Return	Volatility	Sharpe Ratio	Max Return	Min Return	VaR	Cum. Ret.	Drawdown	Positive Days
Long-Short	8.77%	20.31%	0.432	80.05%	-18.65%	-3.40%	189%	-33.81%	51.00%
Long-Only	10.64%	20.30%	0.524	34.25%	-35.53%	-3.80%	288%	-51.15%	54.47%
Market	9.98%	20.82%	0.479	35.12%	-37.64%	-3.94%	244%	-52.00%	53.79%

Graph 6 – Second Period cumulative Returns of the

During the second period, the data present in Table 12, examines the performance during the second period spanning from 01-01-2008 to 31-10-2023. The performance of the *Long-Short* dropped below the market, resulting in lower annual returns and Sharpe Ratio.

Unexpectedly, 2020 was the best-performing year for the *Long-Short* portfolio with an 80.05% return. This second period was also marked by the 2008 Financial crisis where *Long-Only* and the Market faced their worst yearly performances. The *Long-Short* portfolio proved to be more resilient, with a lower VaR and drawdowns, registering better minimum annual returns of -18.65% only in 2012.

Table 13 - Second Period Portfolio Regression

Portfolio	*CAPM*			*FF3*				
	Info Ratio	**Alpha**	**Mkt Beta**	**Info Ratio**	**Alpha**	**Mkt Beta**	**SMB Beta**	**HML Beta**
Long-Short	0.031	0*	-0.001*	0.032	0*	-0.002*	0.002*	0
Long-Only	0.003	0	0.01*	0.004	0*	0.009*	0*	0.001*

*t-statistics is significant ** Analysis done for a 5% significance level

The *Long-Short* approach displays a superior Information Ratio in both the CAPM and the FF3 Model. As seen before the alpha is statistically significant, but an irrelevant value as it is close to 0. The *Long-Short* portfolio reveals a meaningful negative Market Beta and a positive association with the SMB factor, preferring returns of small companies. The connection with the HML factor is insignificant.

4 Conclusion

The results demonstrate that for a comparable signal, provided but the MRTS 452 – General Merchandise Stores, over a longer timeframe of the last 32 years, it wasn´t able to generate similar risk-adjusted performance for the Consumer Discretionary/Durable Sector. Although the other 12 Industry sectors from Fama-French have had excellent performance, under this period, their combinations couldn’t, many times beat the returns achieved by the Market. The best approach would be the combination of these signals into one portfolio, as used in the *Long-Short*, to increase the diversification and risk mitigation effects, but also to profit in the good and the bad times of the Market, as remarkably it attained a lower volatility and a higher Sharpe ratio.

The *Long-Only* Portfolio excelled in returns and offered lower volatility resulting in the best risk-adjusted performance in the full period but didn’t generate a high alpha and information ratio. Compared to the *Long-Short*, which had better downside risk, with less extreme minimum annual returns, Value at Risk, and drawdowns, surprisingly this portfolio did generate a higher information ratio thus achieving a higher excess return. The signal applied, not only on a sector basis, but in this portfolio could also stress test the belief of the efficient hypothesis, as returns also peaked at values much higher than those obtained by the market.

Thus, the *Long-Short* portfolios offer a compelling investment approach by leveraging the diversification strengths even when the backtest results reveal that *Long-Only* had better returns in the past when both were tracked against the Market, but as always, the optimal decision is made based on the investor's preferences. The *Long-Only* approach could be easier to implement but a risky investor also wants extreme returns for a comparable level of risk, as attained by the *Long-Short* which is seemingly better positioned in down moments.

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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

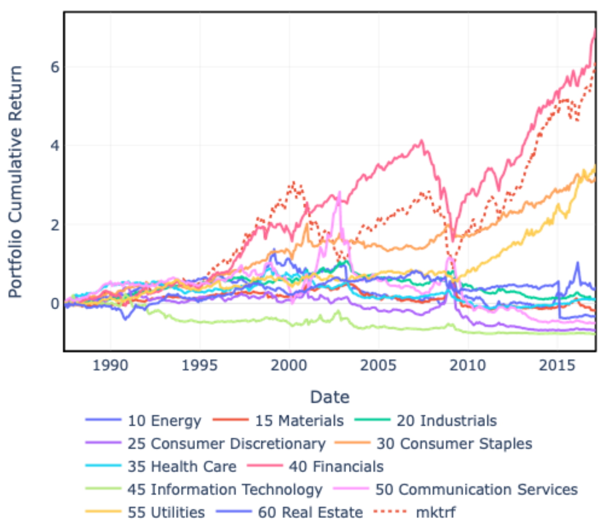


Table 2: Performance Metrics

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

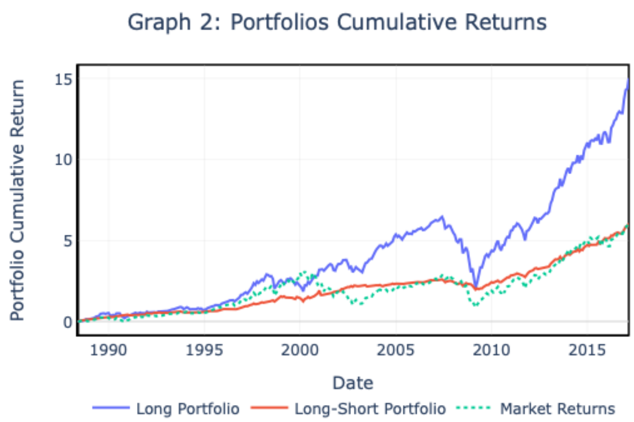


Table 3: Portfolios Performance metrics

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

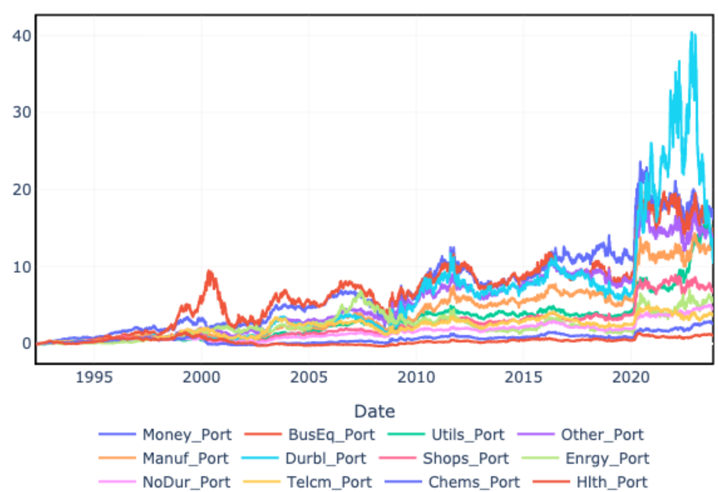
Table 5: Performance Measurements

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*.

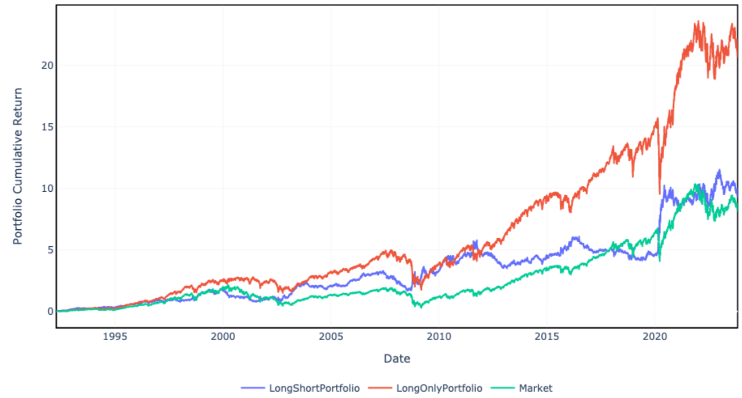
2.2.4 Portfolios' Performances

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

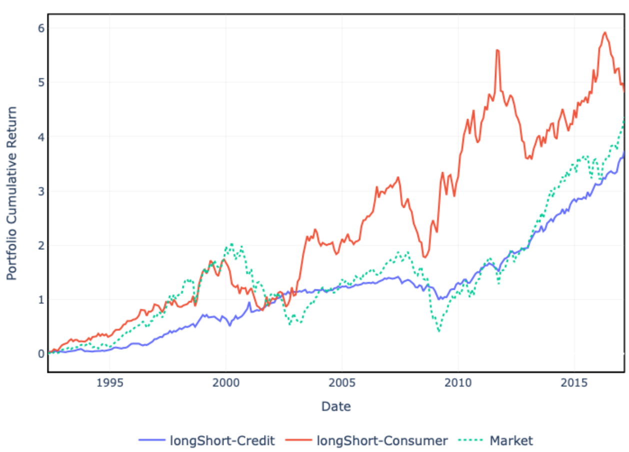


Table 7: Portfolios Performance metrics

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.

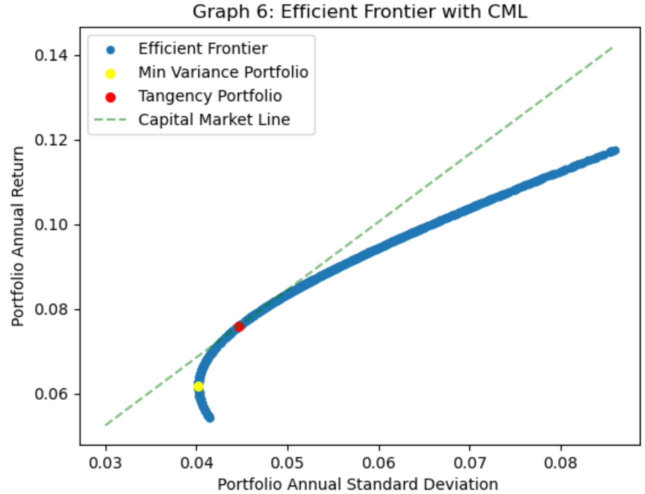
The correlation coefficient of 0.11 between the two strategies stands at an impressively low. This suggests that the strategies tend to move independently of each other, thereby fostering a high level of diversification and risk mitigation as the individual strategies are less likely to experience synchronized 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.

Graph 6: Efficient Frontier with CML



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.

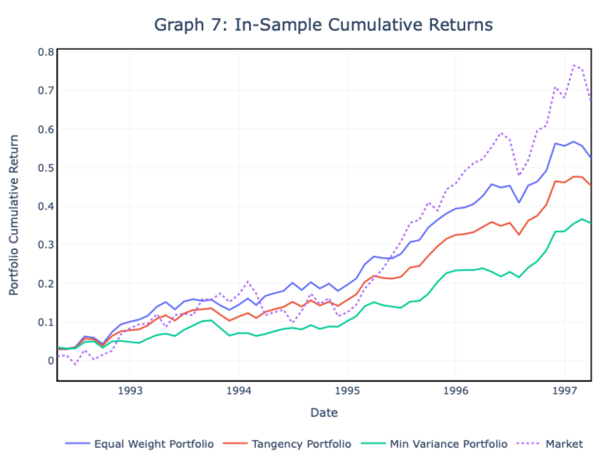
Having established the in-sample period, we then proceeded to the out-of-sample evaluation over the subsequent 20 years, spanning from 1997 to 2017. In this phase, we conducted a comparative analysis, assessing the performance of the *Equal-weighted, Tangency,* and *Minimum Variance Portfolios* against 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.

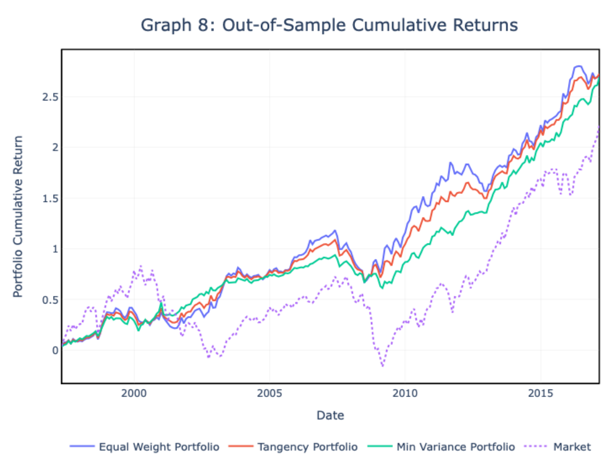
3.3 Results

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





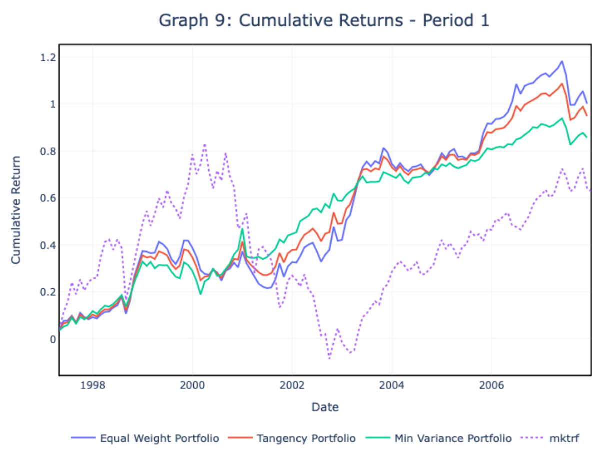
In the in-sample, the weights assigned during this period remain consistent in the subsequent out-of-sample phase. Despite the inherent forward-looking bias in this approach, it provides insights into the performance of the previously calculated optimal weights during the designated time frame. Hence, 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%.

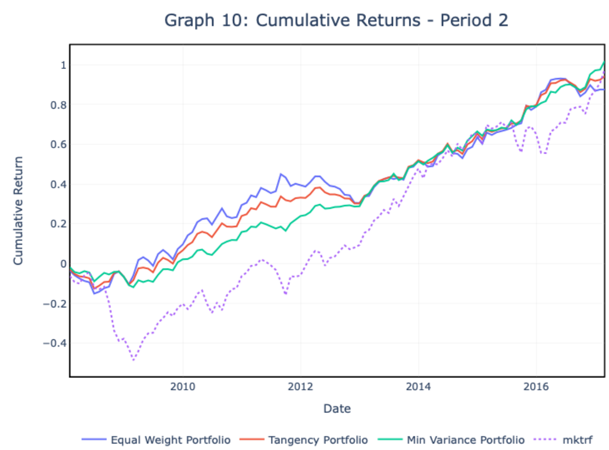
In the out-of-sample analysis, which encompasses the next 20 years, the annual returns of the three portfolios were closely contested and higher than those achieved by the market. However, the *Minimum Variance Portfolio* stood out due to its distinctive characteristic: its Sharpe ratio is the only one 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

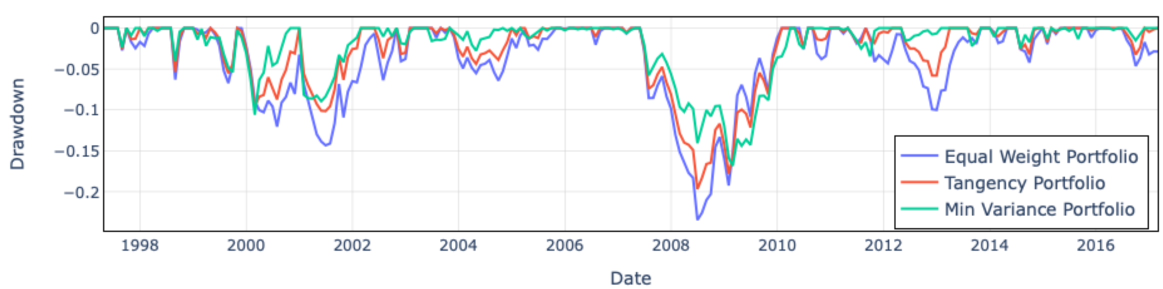
	PERIOD 1			PERIOD 2		
	Equal Weights	**Tangency**	**Min. Variance**	**Equal Weights**	**Tangency**	**Min. Variance**
Alpha	0.004	0.004	0.004	0.006	0.006	0.005
	(2.076)	(2.420)	(2.697)	(2.522)	(3.141)	(4.106)
Mkt-Rf	0.270	0.252	0.227	0.065	0.132	0.228
	(5.264)	(6.138)	(6.840)	(1.164)	(3.119)	(7.611)
SMB	-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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