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ANALYSIS OF QUANTITATIVE INVESTMENTS STRATEGIES- **INVESTORS'**
EXPECTATIONS: IS A COMPANY WITH A HIGH SALES GROWTH RATE A GOOD
INVESTMENT OPPORTUNITY?

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Abstract

Sales growth rate emerges as a key financial signal, correlating positively with stock price performance and serving as a leading indicator of a company's prospects. The study integrates corporate life-cycle theory to underscore variations in financial stability over a company's lifespan. Core to the analysis is the construction and evaluation of portfolios based on sales growth rate and current ratio, revealing promising *Long-Only* strategies through extensive performance assessments and financial models.

Despite acknowledged limitations, including the challenge of annual financial data, the study contributes to a nuanced understanding of risk-adjusted returns and the dynamic interplay of market factors in portfolio construction.

Keywords: Investment management, financial signals, sales growth rate, portfolio strategy, corporate life-cycle theory, risk-adjusted returns, financial stability, Long-Only portfolios, volatility-timing strategy, Fama-French Three-Factor Model, performance analysis, market dynamics, portfolio construction, leading indicators.

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1- Introduction

1.1. Signal Overview

In the world of investment management, the selection of appropriate financial signals for portfolio strategy is a critical endeavour. This chapter provides an in-depth exploration of the rationale and significance of choosing sales growth rate as a key financial signal for constructing investment portfolios.

Sales, in its simplest form, refers to the act of selling a product or service to a customer. The transfer of ownership is usually completed in exchange for money or an agreed-upon value (True Tamplin, 2023). It is a central element in financial analysis and is considered a vital indicator of a firm's overall health and growth potential.

Sales growth rate serves as a key factor in the growth-value dilemma. It assists investors in identifying companies with strong growth potential, which are often associated with higher future cash flows and increased shareholder value. It can indicate whether a company is growing, stagnating, or experiencing a decline in its core business activities.

Numerous studies have explored the relationship between sales growth rate and stock returns. Academic research has consistently demonstrated a positive correlation between sales growth rate and subsequent stock price performance. This empirical evidence substantiates the theoretical argument that sales growth rate can serve as a valuable signal for portfolio strategy.

Sales can be a reliable indicator of a firm's performance, but it's important to recognize that it has limitations and should be considered alongside other financial and operational metrics for a more comprehensive assessment of a company's health. Focusing solely on sales doesn't reveal how efficiently a company is managing its costs.

1.2. Economic Motivation

Kipliyah (2021) concluded that sales growth rate can serve as a leading indicator of a company's prospects. By focusing on this metric, investors can potentially identify promising

opportunities ahead of broader market recognition. The continuous increase in sales growth is an attraction for investors to invest as this will increase the share price of companies and it will be reflected in the company's value.

Companies with high sales growth are seen as having the readiness to compete and accompanied by an increase in the market share that directly increases the value of the company (Limbong & Chabachib, 2016).

Also, sales growth generally utilizes capacity more fully, which spreads fixed costs over more revenues resulting in higher profitability. Alternatively, if an industry has increasing economies of scale, growing firms benefit from such effects, again increasing performance. Depending on the industry structure, sales growth may also provide additional market power which firms can use to increase performance (Brush et al., 2000).

Nevertheless, Brigham & Houston (2018) demonstrated that because the sales growth rate encourages the value of debt or equity contained in the Capital Structure, it will be a concern for investors because from the capital structure it will be seen where the company gets funds from. A debt ratio that is too high will create the possibility of default and bankruptcy and will become a concern for investors.

In the context of investment analysis, understanding the corporate life cycle is pivotal for constructing robust portfolios. Companies evolve through distinct phases, each characterized by unique risk profiles and financial dynamics. In the early "Introduction Stage," companies face great financial difficulties, often marked by high debt ratios and lower profit margins. Recognizing that firms have challenges and opportunities at different life-cycle stages, a strategic approach incorporates the current ratio as a complementary signal to sales growth rate in investment analysis. While sales growth rate provides insights into a company's potential for expansion and market competitiveness, the current ratio offers a crucial dimension by assessing its short-term liquidity and ability to meet immediate obligations. This combined analysis

ensures a more comprehensive evaluation, addressing both long-term growth potential and short-term financial health in the ever-changing landscape of investment decision-making.

Evidence show that firms face higher bankruptcy risk at the introduction, growth and decline phases of the life cycle, while risk is lower at mature stage. Also, as compared to the Introduction stage, firms are financially more stable during the Growth stage of firm life cycle (Akbar et al., 2019).

2- Strategy Analysis

2.1. Portfolio's strategies description

The main objective of this study will be to comparatively analyse the financial performance of 10 different portfolios, from 2000 until 2022.

This chapter delineates the methodology and rationale behind the development of the distinct portfolios tailored to exploit opportunities in the financial markets. These portfolios are meticulously crafted to capitalize on two critical financial metrics: sales growth rate and current ratio.

Not considering the market portfolio that will be used as a benchmark, it is important to note that we can divide the other 9 portfolios created into 3 groups. The first derives from a combination between the stocks of companies that simultaneously present the highest sales growth rate values and the highest current ratio values. The second is based only on the stocks of companies that have the highest sales growth rate values and, finally, there is a group focused on the stocks of companies that have the highest current ratio, ignoring the other parameter. In this way, we can show whether the combination of the two signals is relevant for creating this investment strategy.

In all groups, the way to build the different portfolios is identical. A *Long-Only* portfolio will be created, to focus on a portfolio with the characteristics that we believe are ideal for better performance. This portfolio will be composed by taking a long position on the

top tercile of companies identified as ‘Tercile 0’. To make a distinction, this strategy is called *Long-Top*.

A *Long-Only* portfolio on the bottom tercile of the companies will also be created, aiming to identify investment opportunities among companies that are currently undervalued or facing challenges. This strategy assumes that the market may have overlooked the potential for improvement in these companies. In the same models, this strategy is called *Long-Bottom*.

Finally, a *Long-Short* portfolio will be created, to generate returns by exploiting differences in the performance of these two sets of investments, as well as market portfolio, which will serve as a benchmark against which the performance of the actively managed portfolios is evaluated.

It is important to note that to build the 3 strategies, 3 different rankings were created, namely, a ranking for the sales growth rate, a ranking for the current ratio, and a combined ranking between these two parameters. The latter is built based on the combined results of the first two rankings, with the lowest value corresponding to the company with the highest sales growth rate and highest current ratio simultaneously.

Furthermore, the division of terciles is done annually and for each of the rankings created. More specifically, and as an example, for the year 2000, companies that fall into the tercile originated based on the ranking of highest sales growth rate may not be the same as the same ranking in 2002 and may not be the same as the one created for 2000 but for the combined ranking between the two identified signals.

In this study, all portfolios are equally weighted, ensuring that each stock in a portfolio carries the same weight. This approach is adopted to eliminate biases stemming from uneven capital allocations, enabling a straightforward risk assessment.

Also, to build all portfolios, we only consider sales growth rate and current ratio values greater than or equal to 0.

2.2. Data

The database used for this study was taken from *Compustat*. This platform provides relevant data for the analysis, namely the value of Sales/Turnover, and the value of Current Assets and Current Liabilities for each company for each year.

From this data it was able to construct the two highlighted signals. More explicitly, with the Sales/Turnover value we were able to calculate the Sales Growth Rate for each company, for each year, except for the first year of observations (2000) which will not be used for analysis for this reason. The methodology behind building is stated in *Equation 1*:

$$\text{Equation 1} - \text{Sales Growth Rate}_{it} = \frac{\text{Sales/Turnover}_{it} - \text{Sales/Turnover}_{i(t-1)}}{\text{Sales/Turnover}_{i(t-1)}}$$

Finally, we constructed the current ratio from the data on current assets and current liabilities. This ratio serves as a crucial indicator of a company's ability to meet its short-term obligations. By comparing the liquidity of a firm's assets to its current obligations, stakeholders gain insights into the company's capacity to cover immediate financial needs.

$$\text{Equation 2} - \text{Current Ratio}_{it} = \frac{\text{Current Assets}_{it}}{\text{Current Liabilities}_{it}}$$

The data used for the regressions and for the risk-free rate was obtained from the Kenneth R. French Data Library.

2.3. Performance Analysis

2.3.1. Graphical Analysis

The first metric used to analyse the portfolios created is a graphical combination of the cumulative returns of the 10 portfolios.

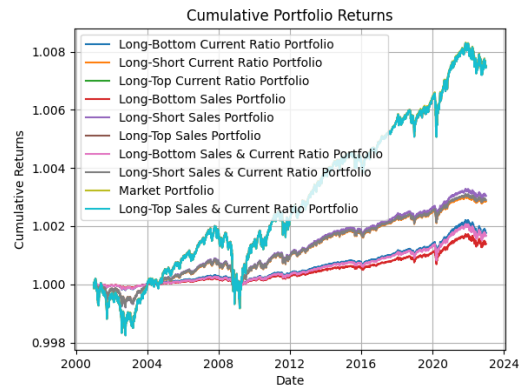


Figure 1: Portfolios' Cumulative Returns

The graphical analysis reveals intriguing dynamics in the performance of various portfolios over the sample period. Initially, all portfolios outperformed the market, with the *Long-Bottom Sales and Current Ratio portfolio* standing out. However, the benchmark consistently exhibited stronger overall performance, particularly in recent years.

Notably, both the *Long-Short* and *Long-Bottom* portfolios displayed diminishing returns, marked by a peak followed by a significant decline around the 2007/2008 period. This trend may be associated with the housing market bubble, fuelled by lax lending practices and the proliferation of subprime mortgages, peaked around 2006. Consequently, the global financial crisis of 2008 emerged, triggered by the collapse of major financial institutions and the freezing of credit markets, which had a severe impact on stock markets and investor confidence.

A nuanced shift is observed between the two halves of the sample period. In the initial years, none of the portfolios achieved cumulative returns surpassing 1.004, potentially influenced by economic events such as the dot-com bubble crash, which negatively impacted confidence in financial markets, especially for internet industry companies.

In contrast, the latter half, especially around 2017/2018, witnessed positive and more substantial cumulative returns for portfolios, notably the *Market Portfolio* and *Long-Top portfolio*. This surge is linked to the Tax Cuts and Jobs Act, signed into law in December 2017, which included significant corporate and individual tax reductions.

However, recent years (2019/2020) experienced a decline in portfolio returns, attributed to the outbreak of the COVID-19 pandemic, leading to widespread lockdowns, economic disruptions, and a sharp decline in overall economic activity.

To complement the graphical analysis of these portfolios, a volatility timing strategy was created by applying a constant leverage of 10% annualized volatility to the returns of the portfolios.

The chosen approach involves setting a fixed target volatility (10% in this study). This target serves as a benchmark against which the performance of various portfolios is assessed, to understand how the portfolios respond to changes in market volatility and whether such adaptations lead to improved risk-adjusted returns. The examination of cumulative returns over time serves as a visual narrative, allowing for the identification of patterns, trends, and potential anomalies in the context of volatility-timing.

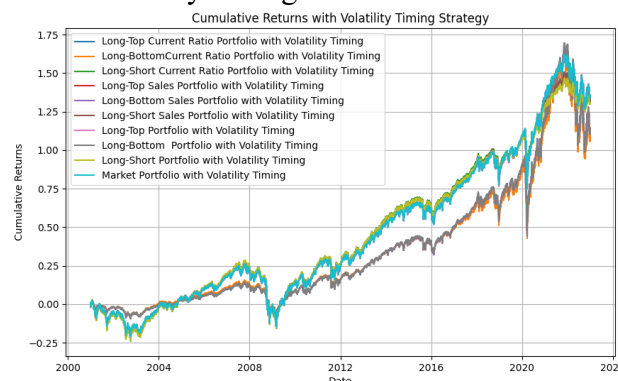


Figure 2 Portfolios' Cumulative Returns with Volatility-Timing Strategy

Looking at the graphical representation, we can observe that applying this volatility-timing strategy limits all portfolios, in the sense that it implies that they have negative cumulative returns, but it also provides a higher maximum value of cumulative returns, reaching values close to 2.

Despite incurring negative cumulative returns, the strategy exhibits a notable characteristic of achieving higher maximum cumulative returns compared to the previous approach. This paradoxical outcome underscores the nature of the financial markets, where the pursuit of reduced volatility may not always align with immediate positive returns.

The negative cumulative returns suggest potential challenges in consistently navigating the dynamic market conditions. However, the strategy's ability to attain elevated maximum cumulative returns implies an adeptness in capitalizing on transient opportunities during periods of heightened volatility. Thus, we identify a trade-off between short-term losses and the strategic capture of favourable market conditions, reflecting the complex interplay between risk mitigation and return optimization within the context of the chosen volatility-targeted investment strategy.

Regarding portfolio trends, we found that all portfolios present a more similar behaviour to our benchmark. Thus, we can conclude that the timing-volatility strategy is effective in replicating the market's returns, and the portfolios' returns are highly correlated with the benchmark.

2.3.2. Performance Indicators

From this moment on, we must consider a division of sample periods. The division of the analysis into distinct in-sample and out-of-sample periods, spanning from 2000 to 2015 and 2016 to 2022, respectively, is rooted in a methodological commitment to robustness and generalizability. The in-sample period, encapsulating significant historical market events and economic cycles, serves as the foundation for strategy development and parameter optimization. Subsequently, the out-of-sample period, representing a distinct and more recent market environment, functions for testing the strategy's efficacy and adaptability. This demarcation allows for a comprehensive evaluation of the strategy's performance beyond the historical data used for its construction. The rationale for this dichotomy lies in the desire to ascertain the strategy's ability to navigate unforeseen market conditions, providing a more robust indication of its potential real-world applicability and resilience.

Table 1 presents a summary of some performance metrics of the constructed portfolios and the market portfolio, namely the Average Annualized Returns, the Annualized Sharpe Ratios,

the standard deviation, the Skewness, the Kurtosis, and the Maximum Drawdown. These metrics are key to determining the overall performance of an investment portfolio, as they provide an objective measure of how well a portfolio is performing relative to the risk assumed.

Looking first at the results obtained in the in-sample period, in terms of annualized average return, the *Long-Top* portfolios are those that generate the highest return, although not significant. Here, the value of the *Market portfolio* can be replicated by the *Long-Top* portfolio built solely based on the companies' sales growth rate.

Nevertheless, these portfolios are the ones with the highest standard deviation (0.005%), which is still considered a very low volatility value. For investors, a low standard deviation implies that the investment's performance is consistent and less risky, as the returns are closely clustered around the average.

		Performance Indicators					
		Average Annualized Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis	Max Drawdown
In sample	Long-Top Sales & CR Portfolio	0.0287%	0.0050%	0.02291	-0.09152	8.20515	-0.00280
	Market Portfolio	0.0288%	0.0050%	0.02503	-0.09000	8.26734	-0.00282
	Long-Short Sales & CR Portfolio	0.0120%	0.0021%	0.02243	-0.07793	8.05673	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0048%	0.0008%	0.02293	-0.16271	9.06930	-0.00044
	Long-Top Sales Portfolio	0.0288%	0.0050%	0.02450	-0.09180	8.32141	-0.00281
	Long-Short Sales Portfolio	0.0124%	0.0022%	0.02262	-0.08126	8.18907	-0.00122
	Long-Bottom Sales Portfolio	0.0039%	0.0006%	0.02292	-0.15870	9.28426	-0.00037
	Long-Top CR Portfolio	0.0287%	0.0050%	0.02456	-0.09031	8.24690	-0.00281
	Long-Short CR Portfolio	0.0118%	0.0021%	0.02250	-0.07414	7.96206	-0.00117
	Long-Bottom CR Portfolio	0.0051%	0.0008%	0.02295	-0.17022	9.83142	-0.00048
Out Of Sample	Long-Top Sales & CR Portfolio	0.0455%	0.0047%	0.03856	-0.67465	12.65674	-0.00149
	Market Portfolio	0.0457%	0.0047%	0.02964	-0.69033	13.23384	-0.00151
	Long-Short Sales & CR Portfolio	0.0158%	0.0014%	0.04344	-0.71792	12.83809	-0.00046
	Long-Bottom Sales & CR Portfolio	0.0139%	0.0019%	0.03868	-0.57619	12.07289	-0.00057
	Long-Top Sales Portfolio	0.0456%	0.0047%	0.03004	-0.66260	12.40229	-0.00147
	Long-Short Sales Portfolio	0.0170%	0.0016%	0.04228	-0.69587	12.58713	-0.00050
	Long-Bottom Sales Portfolio	0.0116%	0.0015%	0.03856	-0.56676	11.85340	-0.00046
	Long-Top CR Portfolio	0.0455%	0.0047%	0.02872	-0.67846	12.67244	-0.00149
	Long-Short CR Portfolio	0.0155%	0.0014%	0.04447	-0.75402	13.54606	-0.00045
	Long-Bottom CR Portfolio	0.0145%	0.0020%	0.03850	-0.53224	11.29069	-0.00059
Full Sample	Long-Top Sales & CR Portfolio	0.0341%	0.0049%	0.02768	-0.25653	9.42256	-0.00280
	Market Portfolio	0.0342%	0.0049%	0.02494	-0.26140	9.63589	-0.00282
	Long-Short Sales & CR Portfolio	0.0132%	0.0019%	0.02714	-0.16970	9.52100	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0077%	0.0012%	0.02772	-0.63638	23.92324	-0.00057
	Long-Top Sales Portfolio	0.0341%	0.0049%	0.02499	-0.25195	9.43088	-0.00281
	Long-Short Sales Portfolio	0.0139%	0.0020%	0.02737	-0.18365	9.45658	-0.00122
	Long-Bottom Sales Portfolio	0.0064%	0.0010%	0.02769	-0.61602	23.09241	-0.00046
	Long-Top CR Portfolio	0.0341%	0.0049%	0.02433	-0.25634	9.45474	-0.00281
	Long-Short CR Portfolio	0.0130%	0.0019%	0.02727	-0.16510	9.57061	-0.00117
	Long-Bottom CR Portfolio	0.0081%	0.0013%	0.02771	-0.58625	22.45816	-0.00059

Table 1: Portfolios' Performance Indicators

The fact that the *Long-Top* portfolios created are the most attractive for investors can be proven through the sharpe ratio, which presents higher values in these cases. A higher sharpe ratio suggests a better risk-adjusted performance. Although moderate, as it is similar to the

sharpe ratio value of the benchmark used, we can say that we are dealing with well-structured portfolios.

It is also important to note that all portfolios have a negative skewness value, which means that while most returns may be clustered around the mean, there is a higher likelihood of observing extreme negative returns. This conclusion is supported through the kurtosis values.

We verified all these conclusions in the out-of sample period. Thus, of all the portfolios created and analysed, the *Long-Top* portfolio built based only on the highest values of companies' sales growth rates is the most attractive for investors.

2.3.3. CAPM Results

In the context of investment analysis, the Capital Asset Pricing Model (CAPM) serves as a foundational framework for assessing the relationship between risk and return in financial markets. Employing an examination of beta coefficients, the model's key measure of systematic risk, the research navigates through the dynamics of asset pricing, evaluating the performance of diverse portfolios against benchmark indices. Furthermore, the investigation extends to the assessment of alpha values, investigating whether observed returns surpass or fall short of the anticipated returns based on market risk.

CAPM Results										
		Long-Top Sales & CR	Long-Bottom Sales & CR	Long-Short Sales & CR	Long-Top Sales	Long-Bottom Sales	Long-Short Sales	Long-Top CR	Long-Bottom CR	Long-Short CR
In-Sample	Beta	0.99917	0.14855	0.42531	1.00092	0.12542	0.43775	0.99965	0.16238	0.41863
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.36906	0.77079	-0.84009	-0.13219	0.61593	-0.63169	-0.23208	0.64066	-0.69615
	IR	-0.00601	0.01256	-0.01368	-0.00215	0.01003	-0.01029	-0.00378	0.01044	-0.01134
Out-Of-Sample	Beta	0.99451	0.38589	0.30431	0.99176	0.31888	0.33644	0.99380	0.41500	0.28940
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	0.18207	-1.66968	1.67931	0.34743	-1.58737	1.64077	0.17268	-1.63421	1.66752
	IR	0.00434	-0.03983	0.04006	0.00829	-0.03787	0.03914	0.00412	-0.03898	0.03978
Full Sample	Beta	0.99780	0.21858	0.38961	0.99822	0.18251	0.40786	0.99792	0.23692	0.38050
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.20292	0.09699	-0.11282	0.04920	0.08725	-0.07547	-0.13853	0.00246	-0.01382
	IR	-0.00273	0.00130	-0.00152	0.00066	0.00117	-0.00101	-0.00186	0.00003	-0.00019

Table 2: Portfolios' CAPM Results

Looking at the results obtained, we see that the portfolios highlighted in the previous section remain the best strategy.

Long-Top portfolios have a beta approximately equal to 1 that indicates that the portfolio tends to move in line with the benchmark and returns are expected to closely mirror the returns of the benchmark. This can be confirmed through the alpha value obtained, approximately

equal to 0, which suggests that the portfolio's returns are largely in line with what would be predicted by its beta. Furthermore, a negative t-statistic suggests that the alpha is statistically significant, meaning it is unlikely to have occurred by chance. Nevertheless, considering the negative value of the information ratio indicates that the portfolio's active return is not compensating for the level of active risk taken. This result raises concerns about the risk-adjusted performance of the portfolio.

Once again, these results are validated when analysing the same metrics in the out-of-sample period, and the *Long-Top* portfolio built based only on the highest values of companies' sales growth rates is the most attractive for investors.

2.3.4. Fama-French 3 Factors Model Results

The Fama-French Three-Factor Model stands as a cornerstone for comprehensively understanding the drivers of portfolio returns beyond the traditional Capital Asset Pricing Model (CAPM). The outcomes of this Fama-French analysis offer valuable insights into the intricacies of risk and return in investment portfolios, guiding investors and financial analysts in refining strategies to navigate the evolving landscape of financial markets.

Through the table (Table 3: Portfolios' 3 Factors Fama French Results) that displays the results obtained through this last model, the conclusions previously drawn were confirmed.

3 Factors Fama-French Analysis Results										
		Long-Top Sales & CR Portfolio	Long-Bottom Sales & CR Portfolio	Long-Short Sales & CR Portfolio	Long-Top Sales Portfolio	Long-Bottom Sales Portfolio	Long-Short Sales Portfolio	Long-Top CR Portfolio	Long-Bottom CR Portfolio	Long-Short CR Portfolio
In-Sample	Beta_Market	0.99921384	0.14604749	0.42658318	1.00092659	0.12325010	0.43883825	0.99946035	0.15969317	0.41988359
	Beta_HML	-0.00000003	0.00000071	-0.00000037	0.00000001	0.00000063	-0.00000031	0.00000004	0.00000078	-0.00000037
	Beta_SMB	0.00000003	0.00000037	-0.00000017	-0.00000002	0.00000030	-0.00000016	0.00000005	0.00000037	-0.00000016
	Alpha	0.00000000	0.00000001	-0.00000001	0.00000000	0.00000001	0.00000000	0.00000000	0.00000001	-0.00000001
	T-Stat_Alpha	-0.40608326	0.47429421	-0.56460586	-0.10266229	0.30788302	-0.33026025	-0.37515748	0.34398428	-0.43080153
	Information_Ratio	-0.00661724	0.00772876	-0.00920041	-0.00167291	0.00501704	-0.00538168	-0.00611330	0.00560532	-0.00702003
Out-Of-Sample	Beta_Market	0.99420752	0.38451241	0.30484755	0.99122608	0.31767913	0.33677348	0.99352013	0.41314820	0.29018597
	Beta_HML	-0.00000010	-0.00000080	0.00000035	-0.00000017	-0.00000067	0.00000025	-0.00000011	-0.00000103	0.00000046
	Beta_SMB	0.00000007	0.00000026	-0.00000009	0.00000014	0.00000024	-0.00000005	0.00000007	0.00000037	-0.00000015
	Alpha	0.00000000	-0.00000014	0.00000007	0.00000001	-0.00000011	0.00000006	0.00000000	-0.00000017	0.00000009
	T-Stat_Alpha	0.23805171	-1.65286933	1.66265140	0.41154406	-1.56789758	1.62536519	0.22457080	-1.61738865	1.65024542
	Information_Ratio	0.00568050	-0.03944156	0.03967499	0.00982046	-0.03741393	0.03878525	0.00535882	-0.03859491	0.03937895
Full-Sample	Beta_Market	0.99784108	0.21864896	0.38959606	0.99831661	0.18253373	0.40789144	0.99789976	0.23714786	0.38037595
	Beta_HML	-0.00000005	-0.00000078	0.00000036	-0.00000005	-0.00000062	0.00000028	-0.00000002	-0.00000091	0.00000045
	Beta_SMB	0.00000003	0.00000081	-0.00000039	0.00000000	0.00000066	-0.00000033	0.00000004	0.00000087	-0.00000042
	Alpha	0.00000000	0.00000001	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000
	T-Stat_Alpha	-0.20249344	0.06982433	-0.08611768	0.06752326	0.05888318	-0.04531351	-0.15938848	-0.02142031	0.00779763
	Information_Ratio	-0.00272377	0.00093922	-0.00115838	0.00090826	0.00079205	-0.00060952	-0.00214395	-0.00028813	0.00010489

Table 3: Portfolios' 3 Factors Fama French Results

We found that the *Long-Top* portfolios constructed present a beta with the market approximately equal to 1, which means that the portfolio's returns are expected to move together with the overall market. Regarding other betas, we can distinguish 3 different situations.

On the one hand, the *Long-Top* portfolio built based simultaneously on the sales growth rate and the current ratio presents a beta value on the High Minus Low (HML) factor negative and close to 0. This suggests that changes in the relative performance of high book-to-market and low book-to-market stocks are not expected to significantly impact the returns of the portfolio, and that the portfolio may perform relatively better during periods when value stocks underperform growth stocks, and vice versa. Furthermore, this portfolio presents positive beta on the SMB that suggests that changes in the relative performance of small-cap and large-cap stocks may have a subtle impact on the returns of the portfolio, and that the portfolio may perform slightly better during periods when small-cap stocks outperform large-cap stocks.

The *Long-Top* portfolio constructed based on sales growth rates presents a negative and close to zero beta on the SMB, which indicates that the portfolio has low sensitivity to the size factor in the Fama-French Three-Factor Model. In addition, given the positive but close to 0 result of the beta on the HML, this portfolio has no sensitivity to the value factor, which implies that the portfolio's returns are not expected to vary with changes in the value-growth dynamic.

Finally, the *Long-Top* portfolio built based on the current ratio presents positive values in the betas of all factors. In this sense, we can say that the portfolio is not exposed to the specific risk associated with the value-growth spread, and that changes in the relative performance of small-cap and large-cap stocks may have a subtle impact on the returns of the portfolio.

These results are confirmed through the alpha obtained for each portfolio that suggests that the portfolio's returns are consistent with what would be expected given its exposure to systematic risk factors. The negative t-statistic on the alpha suggests that the estimated alpha

is not significantly different from zero, that means that it might have occurred by random chance, and there is not enough evidence to reject the hypothesis that the true alpha is zero.

Once again, the portfolios are not generating excess returns beyond what would be expected based on their active risk exposure.

2.3.5. Drawdowns

To assess the downside risk, we can base ourselves on the analysis of a graphical representation of the drawdowns of the different portfolios. This is a representation of the decline in a portfolio's value from its peak to trough, and serves as a crucial indicator of risk, capturing the real-world impact of market fluctuations on investors' wealth.

Here, we highlight portfolios behaviour during the 2008 financial crisis, with special emphasis on *Long-Top* on the current ratio portfolio, given the magnitude of the peak.

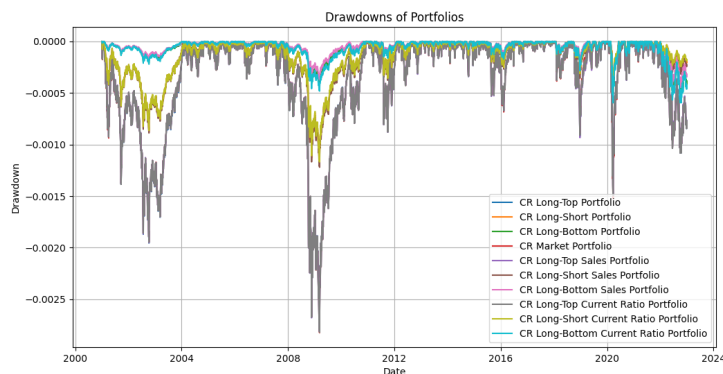


Figure 3: Portfolios' Drawdowns

3- Limitations

When seeking to overcome the complexities of investment strategy implementation, a notable challenge arises arising from a discrepancy in the frequency of financial data and companies' daily returns. While a rich tapestry of daily returns from 2000 to 2022 provides a granular view of market dynamics, the availability of financial data only on an annual basis introduces a pronounced limitation in the untied execution of portfolio strategies, particularly regarding rebalancing.

This incongruity makes it difficult to align rebalancing decisions with the most current financial information, affecting the agility of the strategy in responding to real-time market

conditions. Annual financial data, serving as a basis for portfolio adjustments, introduces a potential delay in information updates, impacting the accuracy and timeliness of weight reallocations. This limitation recognizes the risk of relying on somewhat “obsolete” information and its implications for the responsiveness and dynamism of the strategy.

4- Conclusion

Summarizing, sales growth rate is a pivotal financial signal for constructing investment portfolios within the realm of investment management.

Sales growth rate emerges as a key factor in navigating the growth-value dilemma, aiding investors in identifying companies with robust growth potential and correlating positively with subsequent stock price performance. The continuous increase in sales growth becomes an attraction for investors, potentially leading to increased share prices and enhanced company value.

The portfolios created are designed to exploit opportunities in financial markets and are evaluated through extensive performance analysis. The results obtained consistently highlight the *Long-Top* portfolios as a promising strategy, mirroring benchmark performance and showcasing attractive risk-adjusted returns.

The analysis is extended into distinct in-sample and out-of-sample periods, ensuring robustness and generalizability. The findings hold across both periods, validating the effectiveness of the proposed strategy.

In essence, this thesis contributes to the understanding of portfolio construction strategies, emphasizing the significance of sales growth rate and current ratio as key financial signals. The findings offer valuable insights for investors and financial analysts seeking optimal portfolio management practices, with a focus on risk-adjusted returns and the dynamic interplay of market factors.

References

Abidin, Z., Putra, R., Prabantarikso, M., (2021). “Effect of Capital Structures on Firm Value with Sales Growth and Returns on Sales as Control Variables in Consumer Goods Companies”.

Binus Business Review, 12(3), 225-230

Afgani, E., Rivanda, A., Purbayati, R., Marzuki, M., (2023). “The Effect of Liquidity, Leverage, Operating Capacity, Profitability, and Sales Growth as Predictors of Financial Distress: (Property, Real Estate, and Construction Services Companies listed on the IDX)

Journal Integration of Management Studies, Volume 1, 13-21

Afinindy, I., Salim, U., Ratnawati, K., (2021). “The Effect of Profitability, Firm Size, Liquidity, Sales Growth on Firm Value Mediated Capital Structure”.

International Journal of Business, Economics and Law, Volume 24, 15-22

Akbar, A., Akbar, M., Tang, W., Qureshi, M., (2019). “Is Banckruptcy Risk Tied to Corporate Life-Cycle?”

Sustainability, Volume 11 (678), 1-22

Akmalia, A., Aliyah, S., (2022). “The Role of Financial Performance in mediating the effect of institutional ownership, company size and sales growth on firm value”.

Journal Manajemen Binis, Volume 6 (2), 274-288

Brigham, E., Houston, E., (2009). “The Influence of Profitability, Solvability, Asset Growth, and Sales Growth toward firm value.”

Fundamentals of Financial Management, 12th Edition.

Brush, T., Bromiley, P., Hendrick, M., (2000). “The Free Cash Flow Hypothesis for Sales Growth and Firm Performance”.

Strategic Management Journal, Volume 21 (4), 455-472

Center for Research in Security Prices. [2000-2023]. CRSP US Stock Databases. The University of Chicago Booth School of Business.

Available at: <https://wrds-www.wharton.upenn.edu/pages/get-data/center-research-security-prices-crsp/>

Compustat - Capital IQ. [2000-2023]. Compustat North America Database. S&P Global Market Intelligence.

Available at: <https://wrds-www.wharton.upenn.edu/pages/get-data/compustat-capital-iq-standard-poors/>

Dianova, A., Nahumury, J., (2019). “Investigating the Effect of Liquidity, Leverage, Sales Growth and Good Corporate Governance on Financial Distress.”

Journal of Accounting and Strategic Finance, Volume 2, 143-156

Elviana, E., Ali, H., (2021). “Determination of Financial Distress and Stock Prices: The Effect of Financial Performance and Sales Growth (Financial Management Review Literature)”

Dinasti International Journal of Economics, Finance and Accounting, Volume 3 (3), 241-252

Fama, E.F., and French, K.R., [2000-2023]. Fama-French Research Portfolios and Factors.

Available

at:

https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Giarto, R., Fachrurrozie. (2020). “The Effect of Leverage, Sales Growth, Cash Flow on Financial Distress with Corporate Governance as a Moderating Variable”

Accounting Analysis Journal, 9(1), 15-21

House, C., Benefield, E., (1995). “The Impact of Sales and Income Growth on Profitability and Market Value Measures in Actual and Simulated Industries.”

Developments in Business Simulation & Experiential Exercises, Volume 22, 56-62

Kipliyah, M., Hakimian, (2021). “The Effect of Sales Growth, DPR and ROE on the Value of Food and Beverage Industry Sub-Sector Companies Listed on the IDX 2014-2019 Period.”

International Journal of Innovative Science and Research Technology, Volume 6 (2), 1005-1010

Liviani, R., Rachman, Y., (2021). “The influence of leverage, sales growth, and dividend policy on company value”

Internnational Journal of Financial, Accounting, and Management, Volume 3 (2), 165-178

Pramesti, N., Yasa, P., Ningsih, N., (2021). “The Effect of Capital Structue and Sales Growth on Comppanny Profitability and Value in the Cosmetics Manufacturing and Household Needs Manufacturing Companies”.

Jurnal Ekonomi dan Bisnis Jagaditha, Volume 8 (2), 187-193

Rachmawati, R., Sherlita, E., (2021). “Effect of Sales Growth, Firm Size, Profitability on Earning Per Share”

Turkish Journal of Computer and Mathematics Education, Volume 12 (8), 675-680

Ramezani, A., Soenen, L., Jung, A., (2002). “Growth, Corporate Profitability, and Value Creation”.

Financial Analysts Journal, Volume 58 (6), 56-67

Tamplin, T. 2023, “Are You Retirement Ready?”

<https://www.financestrategists.com/wealth-management/financial-statements/sales/>

Varaiya, N., Roger, A., Weeks, D., (1987). “The Relationship between Growth, Profitability, and Firm Value.”

Strategic Management Journal, Volume 8(5), 487-497

Yuliastari, M., Najmundi, Dewi, M., (2021). “The Influence of Financial Ratios and Macroeconomic Indicators in Predicting Financial Distress (Empirical Study in the Consumer Goods Sector Companies.”

International Sustainable Competitiveness Advantage, 207-217

Appendix

Performance Indicators						
	Average Annualized Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis	Max Drawdown
In sample	Long-Top Sales & CR Portfolio	0.0287%	0.0050%	-0.09152	8.20515	-0.00280
	Market Portfolio	0.0288%	0.0050%	-0.09000	8.26734	-0.00282
	Long-Short Sales & CR Portfolio	0.0120%	0.0021%	-0.07793	8.05673	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0048%	0.0008%	-0.16271	9.06930	-0.00044
	Long-Top Sales Portfolio	0.0288%	0.0050%	-0.09180	8.32141	-0.00281
	Long-Short Sales Portfolio	0.0124%	0.0022%	-0.08126	8.18907	-0.00122
	Long-Bottom Sales Portfolio	0.0039%	0.0006%	-0.15870	9.28426	-0.00037
	Long-Top CR Portfolio	0.0287%	0.0050%	-0.09031	8.24690	-0.00281
	Long-Short CR Portfolio	0.0118%	0.0021%	-0.07414	7.96206	-0.00117
Out Of Sample	Long-Bottom CR Portfolio	0.0051%	0.0008%	-0.17022	9.83142	-0.00048
	Long-Top Sales & CR Portfolio	0.0455%	0.0047%	-0.67465	12.65674	-0.00149
	Market Portfolio	0.0457%	0.0047%	-0.69033	13.23384	-0.00151
	Long-Short Sales & CR Portfolio	0.0158%	0.0014%	-0.71792	12.83809	-0.00046
	Long-Bottom Sales & CR Portfolio	0.0139%	0.0019%	-0.57619	12.07289	-0.00057
	Long-Top Sales Portfolio	0.0456%	0.0047%	-0.66260	12.40229	-0.00147
	Long-Short Sales Portfolio	0.0170%	0.0016%	-0.69587	12.58713	-0.00050
	Long-Bottom Sales Portfolio	0.0116%	0.0015%	-0.56676	11.85340	-0.00046
	Long-Top CR Portfolio	0.0455%	0.0047%	-0.67846	12.67244	-0.00149
Full Sample	Long-Short CR Portfolio	0.0155%	0.0014%	-0.75402	13.54606	-0.00045
	Long-Bottom CR Portfolio	0.0145%	0.0020%	-0.53224	11.29069	-0.00059
	Long-Top Sales & CR Portfolio	0.0341%	0.0049%	-0.25653	9.42256	-0.00280
	Market Portfolio	0.0342%	0.0049%	-0.26140	9.63589	-0.00282
	Long-Short Sales & CR Portfolio	0.0132%	0.0019%	-0.16970	9.52100	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0077%	0.0012%	-0.63638	23.92324	-0.00057
	Long-Top Sales Portfolio	0.0341%	0.0049%	-0.25195	9.43088	-0.00281
	Long-Short Sales Portfolio	0.0139%	0.0020%	-0.18365	9.45658	-0.00122
	Long-Bottom Sales Portfolio	0.0064%	0.0010%	-0.61602	23.09241	-0.00046
	Long-Top CR Portfolio	0.0341%	0.0049%	-0.25634	9.45474	-0.00281
	Long-Short CR Portfolio	0.0130%	0.0019%	-0.16510	9.57061	-0.00117
	Long-Bottom CR Portfolio	0.0081%	0.0013%	-0.58625	22.45816	-0.00059

Table 4: Performance Indicators Results

CAPM Results										
		Long-Top Sales & CR	Long-Bottom Sales & CR	Long-Short Sales & CR	Long-Top Sales	Long-Bottom Sales	Long-Short Sales	Long-Top CR	Long-Bottom CR	Long-Short CR
In-Sample	Beta	0.99917	0.14855	0.42531	1.00092	0.12542	0.43775	0.99965	0.16238	0.41863
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.36906	0.77079	-0.84009	-0.13219	0.61593	-0.63169	-0.23208	0.64066	-0.69615
Out-Of-Sample	IR	-0.00601	0.01256	-0.01368	-0.00215	0.01003	-0.01029	-0.00378	0.01044	-0.01134
	Beta	0.99451	0.38589	0.30431	0.99176	0.31888	0.33644	0.99380	0.41500	0.28940
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Full Sample	T-Stat Alpha	0.18207	-1.66968	1.67931	0.34743	-1.58737	1.64077	0.17268	-1.63421	1.66752
	IR	0.00434	-0.03983	0.04006	0.00829	-0.03787	0.03914	0.00412	-0.03898	0.03978
	Beta	0.99780	0.21858	0.38961	0.99822	0.18251	0.40786	0.99792	0.23692	0.38050
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.20292	0.09699	-0.11282	0.04920	0.08725	-0.07547	-0.13853	0.00246	-0.01382
	IR	-0.00273	0.00130	-0.00152	0.00066	0.00117	-0.00101	-0.00186	0.00003	-0.00019

Table 5: CAPM Results

3 Factors Fama-French Analysis Results										
		Long-Top Sales & CR Portfolio	Long-Bottom Sales & CR Portfolio	Long-Short Sales & CR Portfolio	Long-Top Sales Portfolio	Long-Bottom Sales Portfolio	Long-Short Sales Portfolio	Long-Top CR Portfolio	Long-Bottom CR Portfolio	Long-Short CR Portfolio
In-Sample	Beta_Market	0.99921384	0.14604749	0.42658318	1.00092659	0.12325010	0.43883825	0.99946035	0.15969317	0.41988359
	Beta_HML	-0.00000003	0.00000071	-0.00000037	0.00000001	0.00000063	-0.00000031	0.00000004	0.00000078	-0.00000037
	Beta_SMB	0.00000003	0.00000037	-0.00000017	-0.00000002	0.00000030	-0.00000016	0.00000005	0.00000037	-0.00000016
	Alpha	0.00000000	0.00000001	-0.00000001	0.00000000	0.00000001	0.00000000	0.00000000	0.00000001	-0.00000001
	T-Stat_Alpha	-0.40608326	0.47429421	-0.56460586	-0.10266229	0.30788302	-0.33026025	-0.37515748	0.34398428	-0.43080153
	Information_Ratio	-0.00661724	0.00772876	-0.00920041	-0.00167291	0.00501704	-0.00538168	-0.00611330	0.00560532	-0.00702003
Out-Of-Sample	Beta_Market	0.99420752	0.38451241	0.30484755	0.99122608	0.31767913	0.33677348	0.99352013	0.41314820	0.29018597
	Beta_HML	-0.00000010	-0.00000080	0.00000035	-0.00000017	-0.00000067	0.00000025	-0.00000011	-0.00000103	0.00000046
	Beta_SMB	0.00000007	0.00000026	-0.00000009	0.00000014	0.00000024	-0.00000005	0.00000007	0.00000037	-0.00000015
	Alpha	0.00000000	-0.00000014	0.00000007	0.00000001	-0.00000011	0.00000006	0.00000000	-0.00000017	0.00000009
	T-Stat_Alpha	0.23805171	-1.65286933	1.66265140	0.41154406	-1.56789758	1.62536519	0.22457080	-1.61738865	1.65024542
	Information_Ratio	0.00568050	-0.03944156	0.03967499	0.00982046	-0.03741393	0.03878525	0.00535882	-0.03859491	0.03937895
Full-Sample	Beta_Market	0.99784108	0.21864896	0.38959606	0.99831661	0.18253373	0.40789144	0.99789976	0.23714786	0.38037595
	Beta_HML	-0.00000005	-0.00000078	0.00000036	-0.00000005	-0.00000062	0.00000028	-0.00000002	-0.00000091	0.00000045
	Beta_SMB	0.00000003	0.00000081	-0.00000039	0.00000000	0.00000066	-0.00000033	0.00000004	0.00000087	-0.00000042
	Alpha	0.00000000	0.00000001	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000
	T-Stat_Alpha	-0.20249344	0.06982433	-0.08611768	0.06752326	0.05888318	-0.04531351	-0.15938848	-0.02142031	0.00779763
	Information_Ratio	-0.00272377	0.00093922	-0.00115838	0.00090826	0.00079205	-0.00060952	-0.00214395	-0.00028813	0.00010489

Table 6: 3 Factors Fama French Results

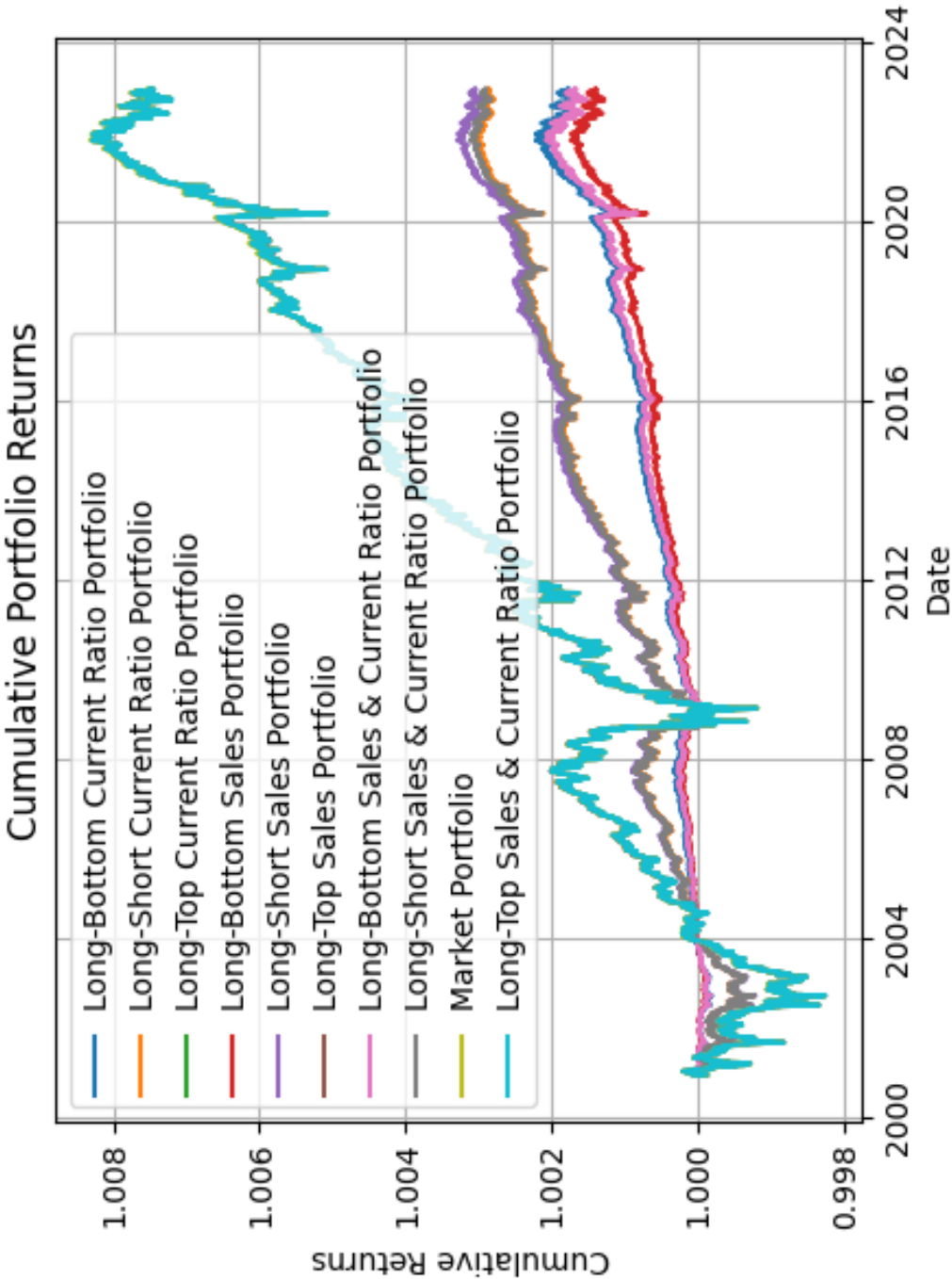


Figure 4: Cumulative Portfolio Returns

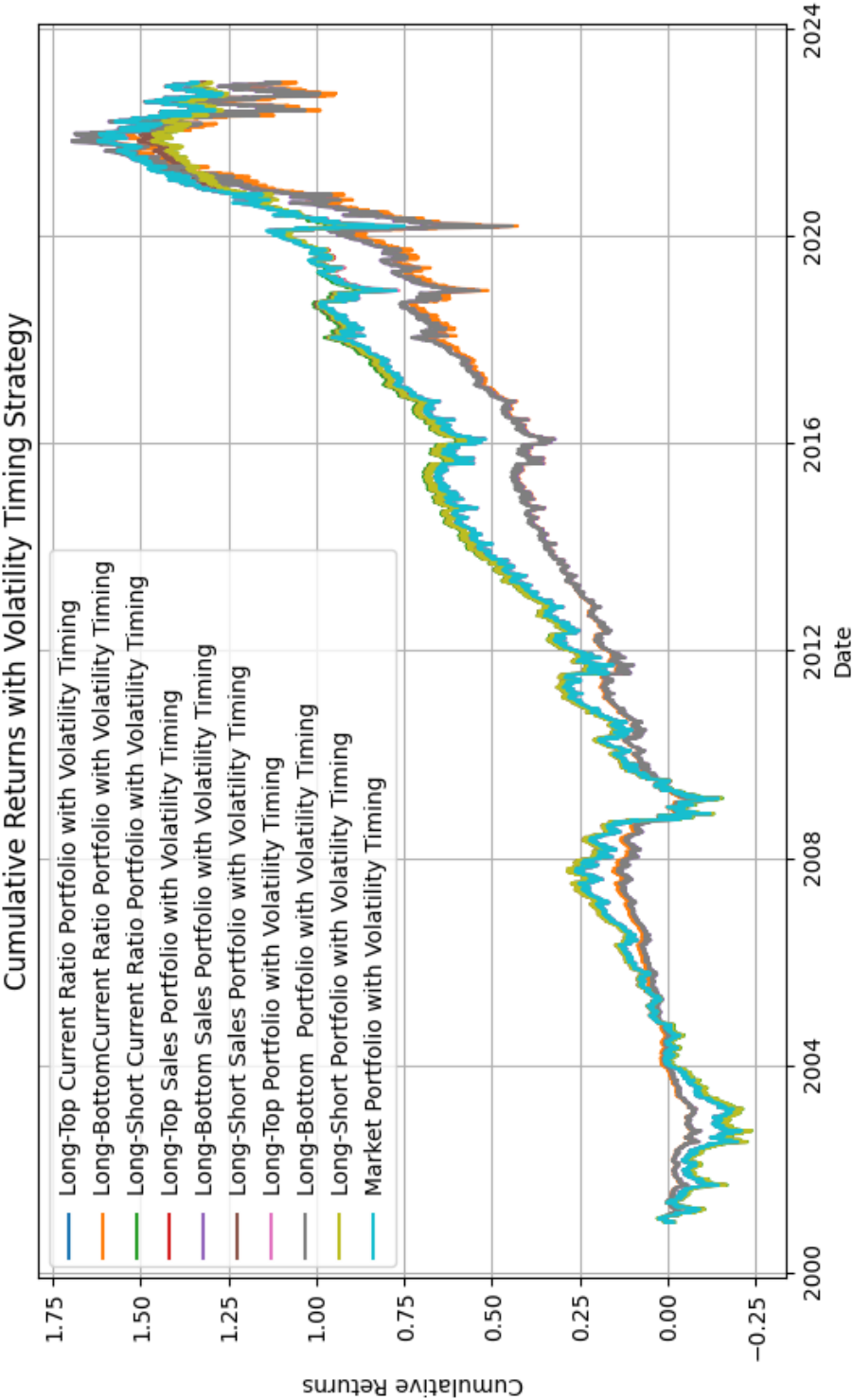


Figure 5: Cumulative Returns with Volatility Timing Strategy

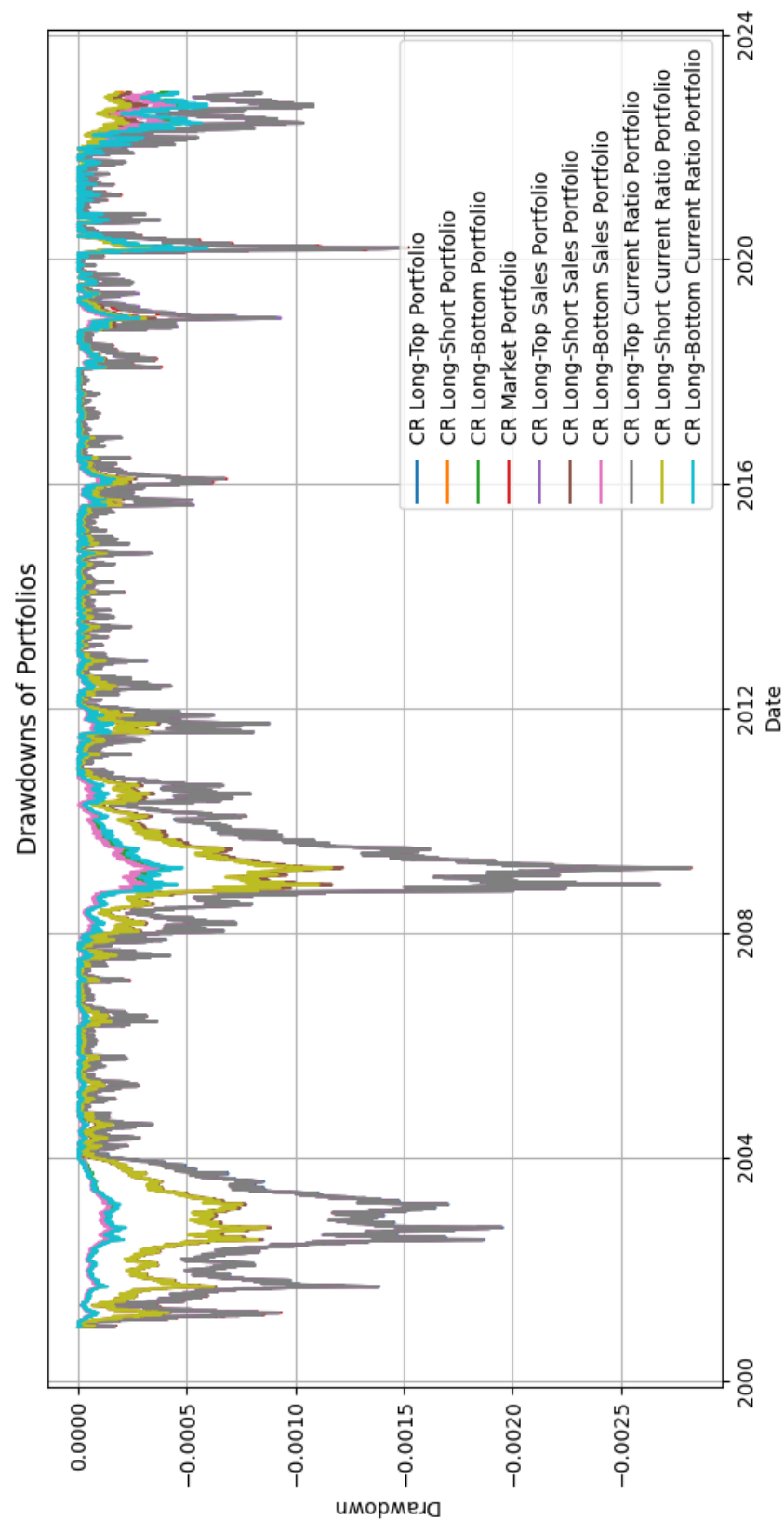


Figure 6: Drawdowns

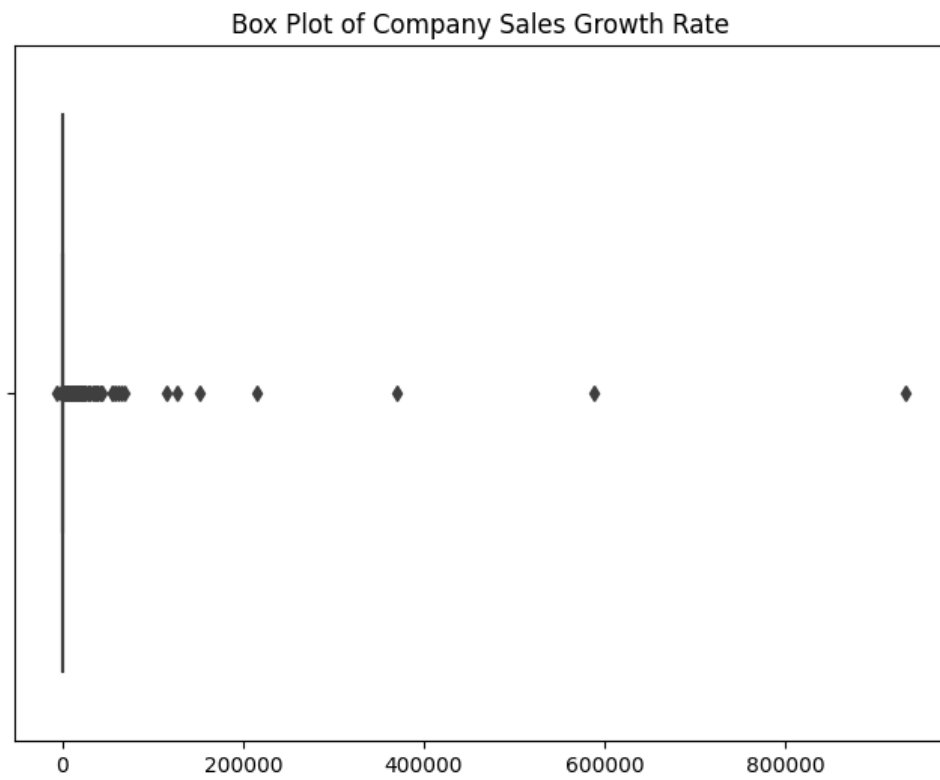


Figure 8: Box Plot Company Sales Growth Rate

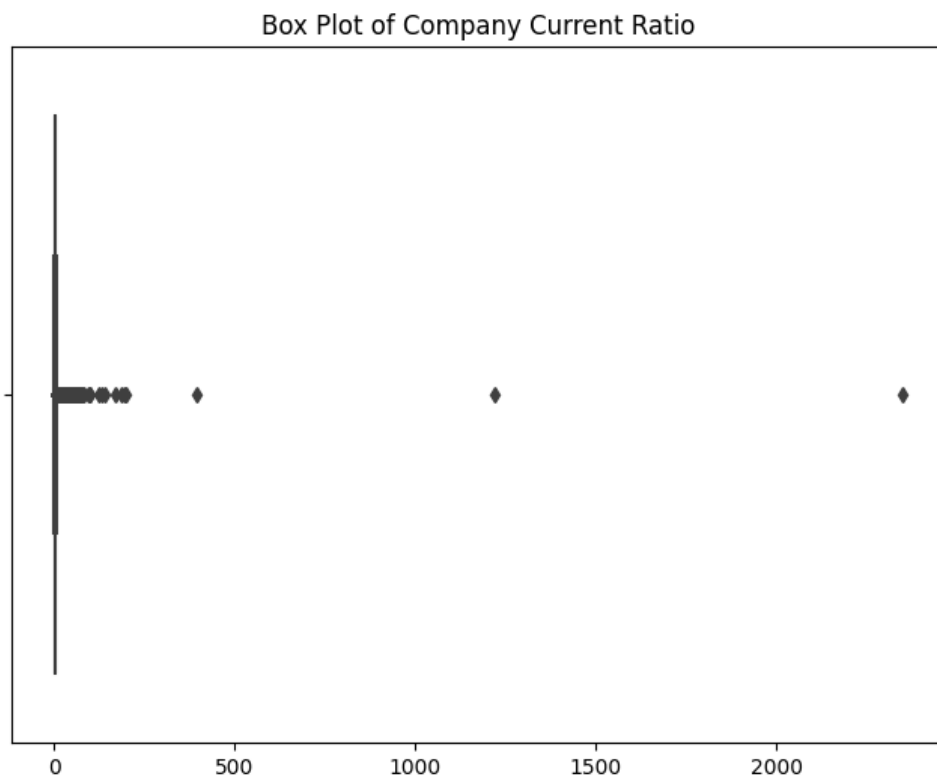


Figure 7: Box Plot Company Current Ratio

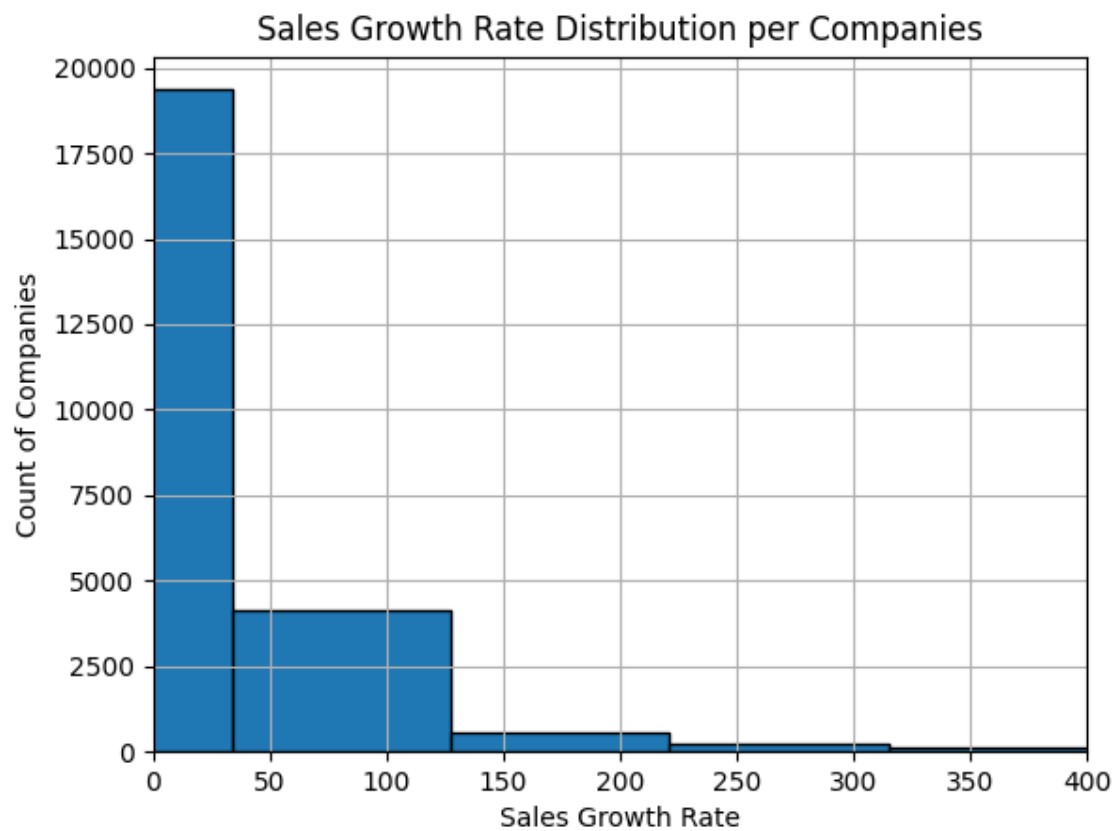


Figure 10: Sales Growth Rate Distribution

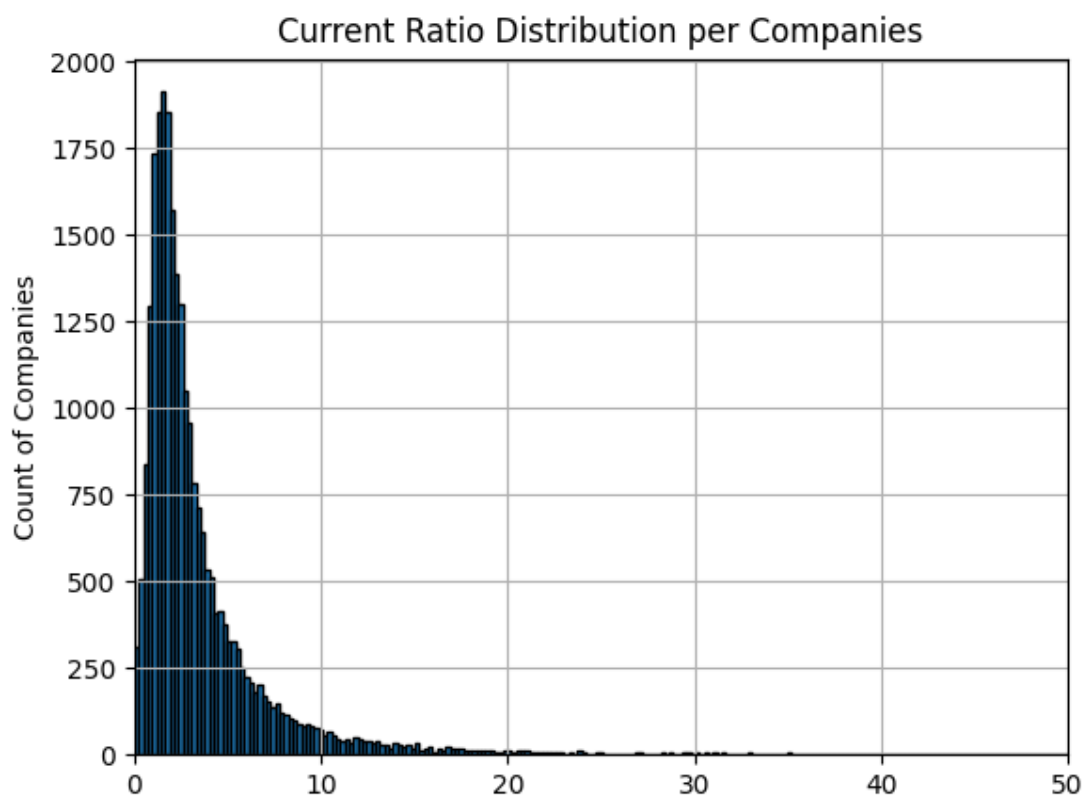


Figure 9: Current Ratio Distribution

Group Part

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.

ANALYSIS OF QUANTITATIVE INVESTMENTS STRATEGIES

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Abstract

This paper aims to effectively combine 5 distinct individual strategies, Tax Surprise, Age ESG + Low-Volatility, Value + Momentum, and Sales into the most optimal portfolio applying four key strategies: the Equally Weighted Portfolio, Minimum Volatility Portfolio, Maximum Sharpe Ratio Portfolio, and Tangency Portfolio. The Maximum Sharpe Ratio strategy stands out with a remarkable risk-adjusted return and consistent positive alphas surpassing every benchmark portfolio particularly well-suited for investors who prioritize in optimizing the balance between risk and return.

Keywords: Investment management, financial signals, sales growth rate, portfolio strategy, corporate life-cycle theory, risk-adjusted returns, financial stability, Long-Only portfolios, volatility-timing strategy, Fama-French Three-Factor Model, performance analysis, market dynamics, portfolio construction, leading indicators.

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1. Introduction

Quantitative investing refers to the use of sophisticated mathematical models and extensive datasets to analyse financial markets and securities, seeking to predict market trends and identify profitable investment opportunities through statistical analysis. Originating in the mid to late 20th century during a period of financial market evolution, quantitative methods have evolved alongside market complexity. Modern quantitative strategies leverage technologies such as artificial intelligence and machine learning, to analyse diverse datasets including financial statements, market sentiment, global economic patterns, and even social media trends to uncover new ways for delivering abnormal returns.

This project aims to effectively combine 5 individual strategies, Tax Surprise, Age, ESG + Low-Volatility, Value + Momentum, and Sales. The following section provides a more detailed exploration of each of these strategies. This analysis brings together the individual strategies into four distinct strategy an Equally Weighted strategy, a Minimum Volatility strategy, a Maximum Sharpe Ratio strategy, and a Volatility Timing strategy. The main objective is to evaluate to which extent these strategies generate meaningful performance results and effectively provide investors with significant risk-adjusted returns.

The report unfolds in the following manner. In Section 2 each individual strategy is introduced detailing the formation of the various trading signals and the selection of the optimal portfolio that will be used in the combined strategies. Section 3 characterizes the data and describes the correlation between the distinct individual strategies. Section 4 illustrates the methodology used for the formation of the four combined strategies.

In subsequent sections, the report conducts a comprehensive performance analysis of the discussed strategy, employing a comparative approach. This analysis involves benchmarking

the performance of the four stated portfolios against four distinct strategies: a traditional 60/40 strategy, an aggressive 80/20 strategy, Market Portfolio and Volatility Timing Strategy applied to the Market Portfolio. Then, the report delves into a detailed regression analysis using two key models: the Capital Asset Pricing Model (CAPM) and an enhanced Fama-French Five-Factor .FF5) model, which incorporates an additional momentum factor. And finally, the report presents a thorough examination of the results, in the two distinct timeframes, in-sample and out-sample period.

2. Individual Strategies

2.1.Tax Expense Surprise and Operating Cash flow

2.1.1. Economic Motivation

The groundbreaking study by Thomas and Zhang (2011) on Tax Expense Momentum marked a pivotal shift in understanding the impact of tax information on stock returns. Their research, the first of its kind, established a positive correlation between tax expense surprise and future stock returns, challenging the traditional focus on contemporaneous returns in most pricing models. This finding is critical, especially considering Gunaydin's (2021) assertion about the predictive power of GAAP accounting statements in developed economies.

The market's initial underreaction to tax expense surprise, as observed by Thomas and Zhang, stems from the complexity and opacity of tax reporting. This underreaction represents a delay in incorporating tax information into stock prices, a gap that savvy investors could exploit. The complexity of tax disclosures, often underestimated by investors, masks the relationship between tax expense and core profitability, leading to a delayed market response upon earnings realization.

Supporting this notion, Hirshleifer et al. (2011) and Moser (1989) highlight the challenges investors face in processing less salient, yet critical, information. This limitation in investor

rationality and attention, particularly towards tax-related data, as shown by Schmidt (2006) and Lev and Nissim (2004), underscores the anomaly in market pricing of tax expense information.

This underreaction to tax expense surprise, backed by the corroborative findings of Ohlson and Bilinski (2015), presents a unique anomaly in the market. It opens avenues for developing investment strategies that leverage this inefficiency for predictive advantage. The tax expense momentum effect, thus, offers a reliable and independent strategy for generating future returns, distinct from earnings surprise, and provides an insightful avenue for quantitative investment strategies seeking to achieve superior returns.

2.1.2. Methodology

The strategy is centered on utilizing the Tax Expense Surprise metric to forecast future stock returns of companies listed on the Nasdaq. This study spans from January 2000 to December 2015 (in-sample) and January 2016 to December 2022 (out-sample), deliberately omitting firms with a market capitalization below \$50 million and including both active and delisted stocks to minimize selection bias.

A key feature of the approach is the monthly formation of decile portfolios based on the Tax Expense Surprise value, a variable positively linked to future returns firstly stated by Thomas and Zhang (2011). In this process, stocks are categorized into deciles each month, corresponding to their Tax Expense Surprise, with higher deciles indicating higher surprises. This categorization is applied to companies that have released their earnings in that month, thus ensuring a timely and relevant grouping.

Portfolios formed are both equal-weight and value-weighted, and they undergo a monthly rebalancing aligned with the earnings release cycle. The focal point of analysis is the subsequent month's returns for each portfolio, providing a direct measure of the Tax Expense Surprise's impact on stock performance immediately following the earnings announcement and

allowing for investors to incorporate this information actionable into their decision-making process.

The strategy further delves into the bivariate portfolio analysis between Tax Expense Surprise and other established market anomalies, such as changes in earnings, sales, cash flow to price ratio, market value, book-to-market ratio, and 12-month momentum. To capture this dynamic, composite score are calculated for each stock every month. This involves standardizing both the Tax Expense Surprise and selected market anomalies and then averaging these scores. For market value (Size), the metric is inverted, particularly to accentuate the performance of smaller firms. Stocks are then reclassified into deciles based on these composite scores, allowing for an intricate understanding of how Tax Expense Surprise interacts with other market factors and influences stock returns.

2.1.3. Results

After analyzing the top 5 Sharpe rating performing strategies, the final strategy the Equal-Weighted Long Short Δ Tax & CF/P was the decided to carry forward on to the group strategy as it was the one that showed the highest robustness after testing in out-on-sample analysis and still managed to conserve a reasonable adjusted return of 0.697 in out-of-sample period from 01-2016 till Jan and yielding 0.856 in in-sample.

Under the CAPM framework analysis the strategy observed a positive alpha of 0.017 for in-sample analysis and 0.014 for out-sample, observing statistically significant alphas on both tested periods registering an in-sample t-statistic of 3.437 and out-sample t-statistic of 2.001. Meanwhile on under FF5 + Mom regression model the portfolio observed a statistically significant positive alpha of 0.012 with 2.434 t-statistic however alpha loses its significance for out-sample with 1.458 t-statistic for the alpha of 0.011.

2.2. Firm Age Strategy

2.2.1. Economic Motivation

Companies are organizations capable of adapting to changing market conditions and external factors that affect their activities, and consequently their performance. This adaptable capacity should prevent companies from aging; However, the existing financial literature indicates that companies tend to age, which results in lower profitability. This aging phenomenon can be attributed to organizational rigidities and rent-seeking behavior (Loderer and Waelchli, 2010).

This study tries to leverage this insight to develop a quantitative investment strategy, using firm age as the primary signal for stock selection. The study is developed by using information regarding the historical performance of the current constituents of the Nasdaq Composite index, over a twenty-year period, from 2000 until 2022. To enhance the strategy, the study explores combining the age signal with information regarding the companies' Research and Development policies, specifically the R&D-to-market ratio, based on the financial literature's suggestion that R&D investment improves profitability (Al-Horani 2003, Bae 2003, Chambers 2002, Duqi 2011, VanderPal 2014).

2.2.2. Methodology

The strategy was established using the signals' data to construct decile portfolios, subsequently used to produce a Long Top-decile, a Long Bottom-decile, and a Long-Short portfolio (taking a long position on the Top-decile portfolio and a short position on the Bottom-decile portfolio), as well as a managed volatility portfolio constructed by applying a volatility timing technique to the age signal Long Top-decile portfolio in an attempt to improve its performance. The signals used to create these portfolios are firm age, combined (combination of the age signal and the R&D-to-market signal), and the alternative combined signal (alternative combination of the age and R&D-to-market signals). The performance of these portfolios was compared with the performance of the benchmark value-weighted portfolio constructed by taking long

positions in all investible securities in the sample (portfolio used as a proxy of the Nasdaq Composite index). A detailed description of the strategy construct, as well as the signals' definition and use to form the decile portfolios, is available in the individual report titled "Age-related Investing – Is Age a Good Predictor of Future Stock Returns?".

The strategy was developed and trained in the in-sample period, from the beginning of the sample period (January 2000) until December 2015 and was tested and validated in the out-of-sample period, from January 2016 until December 2022 (end of the sample period), to ensure the model was well-fitted and to moderate the risk of overfitting.

2.2.3. Results

Both the in-sample and the out-of-sample performance of the portfolios were analyzed in detail in the previously mentioned report. However, their full-sample performance was disregarded, so the following analysis focuses on the strategy's full-sample naive performance and performance on the Fama-French 5-factor model risk factors.

Full-sample naive performance of signals' Long Top-decile, Long Bottom-decile, and Long-Short portfolios, the managed volatility and the Nasdaq proxy portfolios				
		Annualized Average Returns (%)	Annualized Volatility (%)	Sharpe Ratio
Age	Top	45.521	50.336	0.904
	Bottom	15.281	24.618	0.621
	Long-Short	30.24	45.377	0.666
Combined	Top	11.277	40.631	0.278
	Bottom	20.921	23.757	0.881
	Long-Short	-9.643	31.972	-0.302
Alternative	Top	39.878	38.724	1.03
	Bottom	8.671	25.511	0.34
	Long-Short	31.207	34.561	0.903
Age Managed Volatility		51.783	52.572	0.985
Nasdaq proxy	Long-only	17.985	22.398	0.803

Table 1: Long Top-decile, Long Bottom-decile, and Long-Short portfolios, the Managed Volatility, and the Nasdaq proxy portfolios' Performance Indicators Results

Table 1 displays the full-sample naive performance of the strategy's portfolios. The first takeaway from these results is that, as in the in-sample performance, the age signal's Long Top-decile portfolio (composed of the 10% youngest companies in each month of the sample) is, out of the signals' (age, combined, and alternative) portfolios, the portfolio that generates the higher returns (annualized monthly returns of 45.521%), meaning it has the best absolute performance, but it is also the portfolio that generates the most volatile returns (annualized standard deviation of 50.336%), signaling highest risk exposure, findings that are in line with the portfolio's in-sample performance. The difference comes from its risk-adjusted performance because in these terms the best-performing portfolio is the alternative Long Top-decile portfolio, that when compared with the age Top-decile portfolio, generates lower returns (39.878% which is 5.643 percentage points lower than the age portfolio) with lower volatility .38.724% which translates into volatility that is 11.612 percentage points lower than that of the age portfolio), which results in higher Sharpe Ratio (1.030 against 0.904 of the age portfolio). To enhance the satisfactory performance of these two portfolios, it is worth noting that they exceed the performance of the benchmark, represented by the Long-only portfolio (used as a proxy for the Nasdaq Composite index) both in absolute and risk-adjusted terms.

All other portfolios present similar performance to that of the in-sample period. The age Long-Short portfolio generates significant returns, lower than the age Top-decile portfolio due to the positive returns generated by the age Bottom-decile portfolio. The Bottom-decile continues to be the best-performing portfolio out of the portfolios constructed from the combined signal. And, similarly to the age signal, the alternative Long-Short portfolio has a significantly positive performance that is hurt by the moderately positive performance of its Bottom-decile portfolio. Additionally, these full-sample results show that the managed volatility portfolio, based on the age Top-decile portfolio, did not fulfil the expectation of improving the performance of the age portfolio by generating high returns with lower volatility, because although it generated higher

returns and achieved a higher Sharpe Ratio (of 0.985), its returns are subject to higher volatility (meaning higher risk).

Table 2 displays the performance of each signal's best-performing portfolios and the managed volatility and Nasdaq proxy portfolios, on the Fama-French 5-factor model risk factors. The first observation to make from these results is regarding the portfolios' alphas. Because all portfolios generate positive alphas, this means that all portfolios generate returns in excess of the benchmark (in this case over the expected return based on the risk factors), also meaning

Fama French 6 Factors Full-Sample Results					
	Age Top-decile	Combined Bottom-decile	Alternative Top-decile	Age Managed Volatility	Nasdaq proxy
Alpha	0.037	0.012	0.031	0.040	0.011
Alpha T-value	5.158	4.776	6.421	5.556	8.071
MktRf beta	1.250	1.148	1.198	1.481	1.153
MktRf t-value	7.620	19.141	10.757	8.838	8.838
SMB beta	0.834	-0.019	0.647	0.843	0.039
SMB t-value	3.212	-0.1990	3.674	3.183	0.757
HML beta	-0.7140	-0.4790	-0.7110	-0.6780	-0.4350
HML t-value	-2.6370	-4.8390	-3.868	-2.451	-8.057
RMW beta	-0.615	-0.027	-0.485	-0.410	-0.264
RMW t-value	-2.048	-0.250	-2.38	-1.337	-4.409
CMA beta	-0.877	0.089	-0.542	-1.095	-0.108
CMA t-value	-2.147	0.596	-1.953	-2.623	-1.329
R ²	0.421	0.653	0.549	0.446	0.884

Table 2: Fama-French 6 Factors Full-Sample Results

that all portfolios outperform the returns generated from the factors. The portfolios with the highest alphas are the age Top-decile portfolio and its attempted improvement (managed volatility portfolio). Additionally, all portfolios have positive, higher than one, betas on the market meaning that their returns are positively related to the market and their returns are more volatile than the market. All portfolios, except the combined bottom portfolio, are positively related to the returns of smaller companies (positive betas on the size factor). All portfolios are more closely related to growth portfolios (negative betas on the value factor). All portfolios are positively related to the returns of firms with low operating profitability (negative betas on the profitability factor) and the returns of stocks of high investment firms (except the combined bottom decile portfolio).

In conclusion, this study's results verify and support the idea that younger companies tend to outperform their peers and that the firm age signal is a good predictor of future stock returns. Considering the performance of all portfolios created in this strategy, the one chosen to be used in the combined group strategy was the age Long Top-decile portfolio. The main reason for this choice is the high level of returns this portfolio generates (higher than any other portfolio in the strategy apart from its attempted improvement). Although the alternative Top-decile portfolio seemed to be the most rational option because it has the best risk-adjusted performance, it was considered that the age Top-decile portfolio would have a more valuable contribution to the performance of the combined strategy and that the risk associated with its high volatile returns, the main disadvantage of the portfolio, would be diminished with the natural diversification process occurring from combining five independent strategies into one unified strategy.

2.3. ESG + Low-Volatility Strategy

2.3.1. Economic Motivation

Morgan Stanley's "Sustainability Reality" report from early 2023 highlights a robust growth in sustainable funds, with assets under management (AUM) surpassing \$3.1 trillion globally by June 2023 which reflects a sustained demand for sustainable funds.

The underlying motivations for this trend are however quite complex. In a survey where American investors could pick multiple reasons for incorporating ESG criteria into their investment strategy around 51% stated a beneficial social impact, 49% want to keep up with the current market trends and 30% strongly believe ESG investments will outperform the market (Deutsche Bank, 2021).

When asked about the performance of their overall ESG investments in comparison to non-ESG investments in the last 24 months, 30% stated outperformance only 7% affirmed underperformance and whooping 63% declared neither.

Empirical research on the S&P 500 has shown a significant positive link between ESG ratings and risk-adjusted returns, particularly during 2007-2012. This correlation is in part tied to the low-volatility effect, which refers to the phenomenon where against fundamental assumption of modern portfolio theory low-volatility stocks often outperform high-volatility ones over the long term, since higher ESG stocks are often in the low-volatility group. However, a distinct positive ESG impact also exists beyond this low-volatility phenomenon. This relationship strengthens in periods of high market volatility, such as the 2008 financial crises suggesting diversification benefits of ESG stocks (De and Clayman, 2015).

This prompts an inquiry into whether similar trends are observable in a heavily technology growth weighted environment such as NASDAQ.

2.3.2. Methodology

To evaluate the impact of integrating ESG considerations and the low volatility signal into an investor's portfolio within the NASDAQ Stock Exchange Companies firstly ESG annual score data was retrieved from Refinitiv. The selected investment universe is grounded in the Refinitiv NASDAQ Index, a free-float market capitalization-weighted index, that includes a total of 3237 companies.

To accommodate the discrepancy between the annual nature of ESG data and the monthly rebalancing schedule of the portfolios, it is assumed that the ESG score assigned to a company as of the year-end date reflects the company's ESG standing for the entire year.

The financial company-specific data, such as the monthly total return and monthly market capitalization, were computed from the Center for Research in Security Prices (CRSP)

database. This approach ensures consistency in the return data across all individual strategies analysed in the report.

To facilitate comparative analysis, the monthly excess returns are calculated by adjusting for the short-term risk-free rate for the United States. This data is obtained from the Kenneth R. French Data Library, specifically from the Fama-French 5 Factor database that corresponds to the CRSP data.

Upon consolidating the financial and ESG data inaccuracies such as missing values, duplicate values, zero values, extreme outliers, and monthly returns exceeding the 990% were accounted for (Schmidt et al, 2015). Additionally, to ensure the decile creation a key criterion was set: each month must feature a minimum of 10 investable companies. These validation and criteria steps led to a refined investment universe narrowing it down to a total of 1934 investable companies from December 2002 until December 2022.

For this timeframe, best-in-class and worst-in-class portfolios are created by ranking investable assets based on their ESG scores and volatility. These are divided into 10 deciles, with the top and bottom deciles representing the highest (H_ESG) and lowest (L_ESG) ESG scores, and highest (H_Vola) and lowest (L_Vola) Volatility, respectively.

Based on the results of the individual signals, a combined ranking that integrates ESG and Volatility rankings equally is constructed, leading to four unique equal-weighted and value-weighted (VW) portfolio combinations (L_ESG + H_Vola; L_ESG + L_Vola; H_ESG + H_Vola; H_ESG + L_Vola).

2.3.3. Results

Table 3 presents the analysis results across three distinct time periods for the most relevant portfolios: in-sample data from December 2002 to December 2014, out-sample data from January 2015 to December 2022 and the full-sample encompassing the entire range.

Considering the full-sample period, the incorporation of the Low-Volatility signal into ESG portfolios has naturally beneficated results across the board, reducing the annualized volatility for all the portfolios. The highest reduction in annualized volatility occurs in the L_ESG portfolios which decrease 7.05% in Equal-Weighted and 6.44% in Value-weighted Portfolio compared to the H_ESG that reduces 2.74% in the Equal-Weighted and 2.86% in the Value-weighted Portfolio. This is precisely the opposite of what was found in the individual section of this field lab when exploring the European Market. This suggests that the H_ESG portfolio is composed of stocks with lower volatility.

Performance Statistics ESG and Combined Strategy Portfolios				
	Portfolio	Annualized Return	Annualized Volatility	Sharpe Ratio
In-Sample	EW H_ESG	11.31%	19.58%	0.577
	EW L_ESG	9.99%	21.62%	0.462
	VW H_ESG	13.27%	20.52%	0.647
	VW L_ESG	18.89%	21.33%	0.886
	EW H_ESG + L_Vola	8.66%	13.68%	0.633
	EW L_ESG + L_Vola	3.79%	14.78%	0.257
	VW H_ESG + L_Vola	10.68%	14.55%	0.734
	VW L_ESG + L_Vola	13.22%	15.83%	0.835
Out-of-Sample	EW H_ESG	12.51%	17.39%	0.72
	EW L_ESG	-0.10%	18.86%	-0.005
	VW H_ESG	15.11%	16.69%	0.905
	VW L_ESG	20.27%	21.21%	0.956
	EW H_ESG + L_Vola	8.11%	11.45%	0.708
	EW L_ESG + L_Vola	-3.72%	12.50%	-0.298
	VW H_ESG + L_Vola	11.71%	10.95%	1.07
	VW L_ESG + L_Vola	9.73%	14.88%	0.654
Full-Sample	EW H_ESG	12.57%	17.28%	0.727
	EW L_ESG	11.78%	19.84%	0.594
	VW H_ESG	14.52%	17.62%	0.824
	VW L_ESG	20.48%	19.83%	1.033
	EW H_ESG + L_Vola	9.82%	12.67%	0.775
	EW L_ESG + L_Vola	4.73%	13.52%	0.35
	VW H_ESG + L_Vola	11.66%	12.92%	0.903
	VW L_ESG + L_Vola	14.04%	13.95%	1.007

Table 3: Performance Statistics ESG and Combined Strategy Performance Indicators Results

The enhancement in Sharpe Ratios was more selective primarily benefiting the H_ESG portfolios. While the EW_H_ESG saw an increase of 0.048 points and VW_H_ESG an increase of a substantial 0.0785 points the L_ESG portfolios reduced their Sharpe Ratio -0.2438 points in the EW_L_ESG and -0.0260 points in the VW_L_ESG.

Despite the improvements seen in the H_ESG Portfolios, the portfolio with the highest Sharpe ratio remains the VW_L_ESG_L_Vola portfolio, boasting a ratio of 1.007, which still outperforms the VW_H_ESG_L_Vola portfolio's ratio of 0.902741. Yet, when comparing these two portfolios' drawdowns (Figure 1) the VW_L_ESG_L_Vola has not only the highest number of peaks but also the most magnitude of about 9.85% compared to the 2.05% of the VW_H_ESG_L_Vola portfolio.

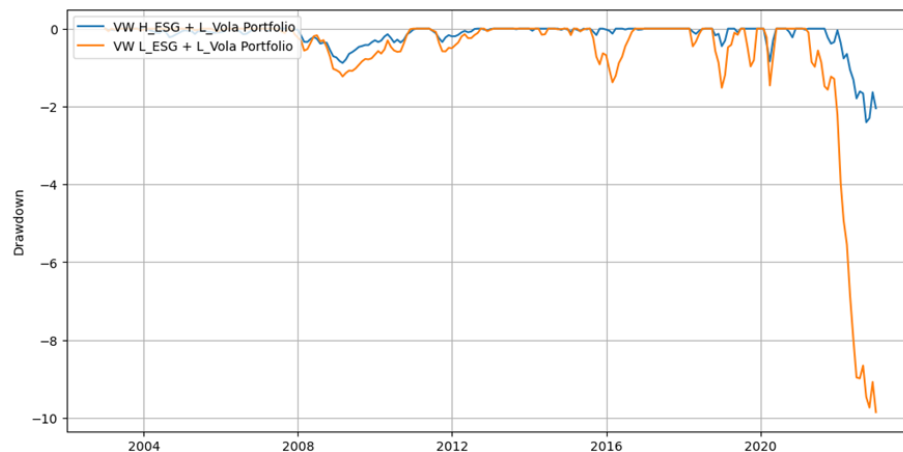


Figure 1: Drawdown of the two best portfolios

Additionally, it is worth mentioning that in the out-sample period the performance of the VW_L_ESG_L_Vola declines significantly. This period is more recent, a time where awareness and interest in ESG investing have notably increased which would explain the observable performance trends. In fact, VW_H_ESG_L_Vola portfolio Sharpe Ratio exhibits a robust 1.070, a 0.4159 increase compared to the VW_L_ESG_L_Vola with 0.6540 in the Out-Sample period.

When analysing these two portfolios performance under the CAPM (Table 4) and the FF5 (Table 5), both provide positive alphas throughout the whole sample which suggests that both investment strategies successfully outperform the market benchmark.

CAPM Regression Results				
Portfolio	Period	Alpha	P-Value	IR
VW_L_ESG + L_Vola	Full-Sample	0.75%	0.000	0.23
	In-Sample	0.89%	0.003	0.24
	Out-Sample	0.38%	0.293	0.11
VW_H_ESG + L_Vola	Full-Sample	0.47%	0.003	0.2
	In-Sample	0.36%	0.177	0.11
	Out-Sample	0.53%	0.004	0.3

Table 4: CAPM Results

FF5 Regression Results				
Portfolio	Period	Alpha	P-Value	IR
VW_L_ESG + L_Vola	Full-Sample	0.87%	0.000	0.28
	In-Sample	1.10%	0.001	0.3
	Out-Sample	0.57%	0.087	0.18
VW_H_ESG + L_Vola	Full-Sample	0.43%	0.007	0.18
	In-Sample	0.31%	0.25	0.1
	Out-Sample	0.45%	0.015	0.26

Table 5: Fama-French 5 Factors Results

During the in-sample period the portfolio VW_L_ESG_L_Vola stands out delivering notably higher excess returns as evidenced by its superior alphas. However, this dynamic shifts in the out-of-sample period, where the gap between alphas of both portfolios is narrower.

Given these considerations, the VW_H_ESG_L_Vola Portfolio has been selected for continued analysis in the strategy evaluation. This choice is underpinned by its robust Sharp Ratio, particularly in the context of the recent surge in ESG investing interest, positive alphas against both the CAPM and FF5 and its superior drawdown performance, signalling its effectiveness in providing risk-adjusted returns.

2.4. Long-Short Value+Momentum Strategy

2.4.1. Economic Motivation

The economic rationale of this study is to examine the performance of synergies between Value and Momentum in recent times and determine whether the benefits related to them remain intact or if they have been influenced and mitigated by the increased volatility and changing conditions of the market. The study's research question is pertinent within the context of financial investment strategies since this synergistic strategy has demonstrated its ability to mitigate the drawbacks that arise when investing solely on Value or Momentum. On one hand, Value investing, grounded in the work of Benjamin Graham and David Dodd (1934), despite its reliance on fundamental analysis, may fail to consider the market's momentum and sentiment-driven movements. On the other hand, Momentum investment strategies, which were solidified as a viable approach by Jegadeesh and Titman (1993), excel at taking advantage of current trends but may overlook the intrinsic value, leading to potential overexposure to overvalued stocks. By combining these two factors, the risks associated with value traps and momentum reversals can be reduced, leading to an improvement in portfolio resilience. Moreover, by combining Value investing, which exploits market inefficiencies and underreactions, with Momentum investing, which capitalizes on prevailing trends and market sentiment, it is formed a merged approach that achieves a balanced investment strategy, an approach potentially beneficial in today's financial markets.

2.4.2. Methodology

The data used in this study is monthly and consists of the stocks listed on the NASDAQ. It spans from the 1st of January 2000 to the 31st of December 2022. The data collected included market capitalization, returns, and book-to-market-ratios. The first two variables were obtained through the CRSP platform and the latter from the Compustat platform.

The data used for the regressions and for the risk-free rate was obtained from the Kenneth R. French Data Library. The factors in the regressions include all NASDAQ, NYSE, and AMEX firms.

For the development of the strategy, an in-sample period spanning from the 1st of January 2000 to the 31st of December 2012 was defined, and to check for the validation of the strategy, an out-of-sample period spanning from the 1st of January 2013 to the 31st of December 2022 was set.

The strategy implemented is based on the methodology of Asness (2013). Therefore, for the construction of the signals, the book-to-market ratio (B/M) was used for Value and the Momentum signal was calculated by taking the past 12 months' cumulative return while skipping the most recent months' returns, MOM2-12. For a comprehensive understanding of the rationale behind the selection of the indicators and a more thorough explanation of the signals, please consult the individual report on Value and Momentum Synergies.

The construction of the portfolios consisted of the ranking of the stocks by their B/M and Momentum, and then assigning them to one of three equals sized terciles: Low, Middle, and High. Afterwards, the returns were value-weighted based on their beginning-of-the-month market capitalization. This resulted in forming three portfolios: Low, Middle, and High for each attribute—Value and Momentum—therefore, six portfolios were created. Subsequently, Long-Short portfolios were built by subtracting the Low tercile from the High tercile and Long-Only portfolios by using the High Tercile for each attribute.

To meet the goal of this thesis, a combination of 50/50 between Value and Momentum was used to create the Value+Momentum (Mixed) Portfolio.

All portfolios are rebalanced monthly and the Market Portfolio, consisting of a Long-Only value-weighted portfolio, was built to use as a proxy of the NASDAQ for performance comparison.

2.4.3. Results

	Momentum Portfolio				Value Portfolio				Mixed Portfolio			
	In-Sample		Out-of-Sample		In-Sample		Out-of-Sample		In-Sample		Out-of-Sample	
	High-Low	High	High-Low	High	High-Low	High	High-Low	High	High-Low	High	High-Low	High
Mean	7.51%	23.47%	17.12%	38.56%	12.13%	24.19%	10.68%	36.94%	10.98%	24.63%	14.38%	38.29%
(t-stat)	(1.61)	(3.82)	(2.15)	(3.40)	(2.53)	(3.51)	(1.58)	(3.71)	(2.84)	(4.18)	(2.02)	(3.68)
Stdev	22.04%	22.44%	28.19%	35.44%	18.91%	25.75%	25.05%	30.09%	14.63%	21.04%	24.81%	31.50%
Sharpe	0.34	1.95	0.60	1.09	0.64	1.02	0.43	1.23	0.75	1.17	0.62	1.22

Table 6: Value and Momentum Portfolios' In-sample vs Out-of-sample Performance

By examining Table 6, the premise that the Long-Short Mixed strategy delivers superior risk-adjusted returns compared to solely Value or Momentum is confirmed based on both the in-sample and out-of-sample outcomes. In the in-sample, the strategy's Sharpe ratio is 0.75, compared to 0.34 for Momentum and 0.64 for Value. During the out-of-sample period, the Sharpe ratio is demonstrated to be 0.62, whereas the Momentum strategy has a ratio of 0.60 and the Value strategy has a ratio of 0.43.

When evaluating the potential benefits of combining Value and Momentum factors in Long-Only strategies, the findings diverge from those of Long-Short strategies. In both in-sample and out-of-sample analysis, the Long-Only Mixed portfolio did not generate higher risk-adjusted returns than if one were to invest solely on Long-Only Value or Long-Only Momentum. Therefore, it was chosen to maintain the Long-Short strategy as the approach to follow and the hypothesis that Long-Only portfolios combining Value and Momentum generate higher returns than solely Long-Only Momentum or Long-Only Value portfolios was invalidated and excluded from further analysis.

The graphical display of the performance of the portfolios' cumulative returns is presented in Figures 2 and 3 below.

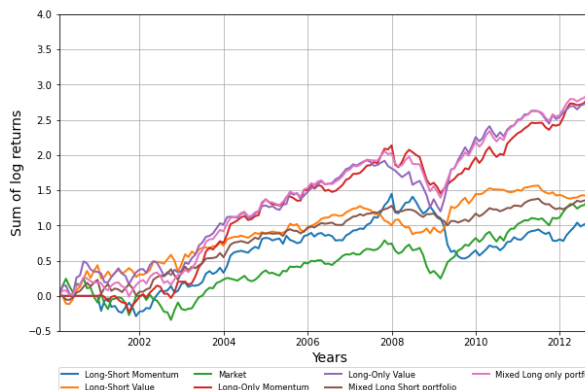


Figure 2: Cumulative Returns of the portfolios In-Sample

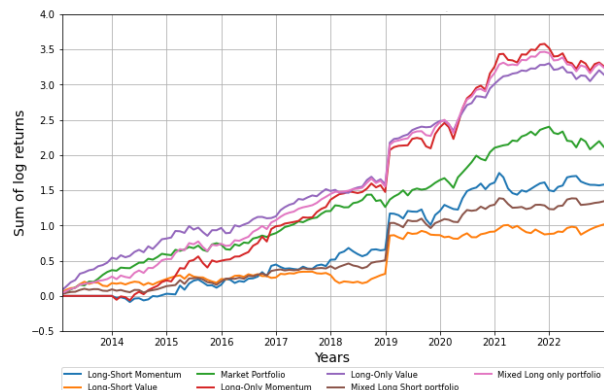


Figure 3: Cumulative Returns of the portfolios Out-of-Sample

In order to improve the visual display of the portfolios' performance and create a more straightforward depiction of cumulative returns over time, the returns were transformed into logarithmic returns and subsequently summed.

CAPM

Regression Results Summary						
	Long-Short Momentum Portfolio		Long-Short Value Portfolio		Long-Short Mixed Portfolio	
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Coefficients						
Constant	0.0085 (1.6958)	0.0146 (1.9076)	0.0110 (2.5220)**	0.0097 (1.4289)	0.0098 (2.9193)*	0.0121 (1.8053)
Mkt-RF	-0.2737 (-2.5992)*	0.1396 (0.8289)	-0.0118 (-0.1280)	0.0707 (0.4716)	-0.1428 (-2.0263)**	0.10519 (0.7090)
Model Statistics						
R-Squared	0.0420	0.0058	0.0001	0.0019	0.0260	0.0042
IR	0.1358	0.1787	0.2020	0.1338	0.2338	0.1690

Table 7: CAPM Results

The symbols "*" and "**" indicate a variable's statistical significance at the 99% and 95% confidence levels, respectively. The values displayed in parenthesis are the t-statistics.

The CAPM regression shows that each strategy consistently exhibits positive average excess returns, and the Information Ratio (IR) indicates that the Long-Short Mixed Portfolio has marginally superior performance compared to Value or Momentum strategies in in-sample.

However, the Capital Asset Pricing Model demonstrates limited explanatory power regarding the market's ability to account for the variations in returns, as showcased by the low R-squared

values. This emphasizes the need to include additional factors in the regression analysis to enhance accuracy. For this purpose, a FF5M+MOM analysis will be conducted next.

FF5M+MOM analysis

The key findings of the regression analysis are displayed in Table 8. It is shown that the inclusion of additional features in the regression led to a significant increase in the R^2 for all portfolios, which indicates a stronger ability of the model to explain the variation in returns. The model demonstrates consistent positive alphas for all strategies including the mix of Value and Momentum, although only showing significance in the out-of-sample period. Regarding the Mixed strategy, in in-sample, three factors prove to be significant, Small minus Big (SMB) at the 5% confidence level, High minus Low (HML) and Momentum (MOM) at the 1%. The most noteworthy finding in this, is the tendency the strategy has towards investing in small caps. This characteristic is associated with Value investing, as these stocks tend to be undervalued and overlooked by the market. Regarding the Information Ratios, the Mixed Portfolio outperforms both Value and Momentum IR's in in-sample and out-of-sample periods, showcasing the benefits of the mix.

	Regression Results Summary					
	Long-Short Momentum Portfolio		Long-Short Value Portfolio		Long-Short Mixed Portfolio	
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Coefficients						
Constant	0.0043 (0.975)	0.0152 (1.989)**	0.0071 (1.663)	0.0129 (1.855)	0.0057 (1.946)	0.0140 (2.057)**
Mkt-RF	0.2078 (1.822)	0.1482 (0.776)	-0.0843 (-0.761)	-0.0609 (-0.352)	0.0617 (0.813)	0.0436 (0.256)
SMB	-0.0658 (-0.436)	0.6616 (1.914)	0.4985 (3.398)*	0.3323 (1.059)	0.2163 (2.153)**	0.4969 (1.611)
HML	-0.0831 (-0.461)	-0.5861 (-1.879)	0.7442 (4.250)*	-0.2377 (-0.840)	0.3306 (2.755)*	-0.4119 (-1.479)
RMW	0.2927 (1.563)	-0.5285 (-1.255)	-0.1049 (-0.577)	-0.3177 (-0.831)	0.0939 (0.754)	-0.4231 (-1.125)
CMA	0.3048 (1.220)	0.7846 (1.713)	-0.2931 (-1.207)	0.4174 (1.004)	0.0058 (0.035)	0.6010 (1.470)
MOM	0.6514 (8.591)*	0.0447 (0.180)	0.1324 (1.797)	-0.4153 (-1.846)	0.3919 (7.767)*	-0.1853 (-0.837)
Model Statistics						
R-Squared	0.398	0.107	0.228	0.068	0.394	0.081
IR	0.085	0.192	0.145	0.179	0.170	0.199

Table 8: Delineating Portfolio Performance with the Fama-French Six-Factor Model

The symbols "*" and "***" indicate a variable's statistical significance at the 99% and 95% confidence levels, respectively. The values displayed in parenthesis are the t-statistics to determine the coefficient's statistical significance.

Maximum Drawdowns

	Max Drawdown (%)		
	Long-Short Momentum	Long-Short Value	Mixed Long Short portfolio
In-Sample	-60.00%	-32.92%	-24.25%
Out-of-Sample	-26.52%	-15.17%	-14.59%

Table 9: Maximum Drawdowns of the Portfolios

One of the main findings of this study is the stabilising characteristics exhibited by the Mixed strategy in the face of market downturns. The evidence presented in Table 9 demonstrates that the Mixed portfolio exhibits more stable characteristics than the Momentum and Value portfolios, both in-sample and out-of-sample. In specific, the Mixed portfolio exhibits a maximum drawdown of -24.25% in the in-sample period, whereas the Momentum and Value portfolios experience drawdowns of -60.00% and -32.92%, respectively. In the out-of-sample period, the Mixed portfolio demonstrates a maximum drawdown of -14.59%, while the Momentum and Value portfolios have drawdowns of -26.52% and -15.17%, respectively. These results indicate that the Mixed portfolio performs better in terms of downside risk and adds an extra layer of resilience when used as an investment strategy. The graphical representation of these performances can be found in the Appendix, in Exhibit 1 and 2.

Overall, these findings present the Long-Short Mixed portfolio as a viable investment strategy, that even though is conditional to market conditions, still benefits from the advantages of the Value and Momentum investing strategies, simultaneously mitigating the drawbacks associated with each and providing more resilience when used as an investment strategy.

2.5. Sales Growth Rate and Current Ratio Strategy

2.5.1. Economic Motivation

This chapter embarks on a comprehensive exploration of the rationale and significance underlying the choice of the sales growth rate as a central financial signal for the construction of investment portfolios.

Sales, in its elementary form, summarizes the fundamental exchange of a product or service for monetary value. A nuanced understanding of sales growth rate becomes imperative as it permeates the fabric of financial analysis, offering insights into a company's trajectory.

The sales growth rate, as a crucial factor in the growth-value dilemma, aids investors in discerning companies with robust growth potential. Such companies are often associated with not only heightened future cash flows but also an augmented shareholder value.

Kipliyah (2021) asserts that sales growth rate as a leading indicator of a company's prospects, offering investors the potential to identify promising opportunities ahead of broader market recognition. The sustained increase in sales growth becomes an attractive proposition for investors, indicating a positive corporate outlook and potentially leading to increased share prices, thereby elevating the overall value of the company.

Companies boasting high sales growth are perceived as not only ready to compete but also poised to increase market share, directly contributing to an enhanced company value (Limbong & Chabachib, 2016). Sales, while being a reliable indicator of a firm's performance, necessitates a nuanced consideration alongside other financial and operational metrics for a comprehensive evaluation of a company's health.

A strategic approach to investment analysis integrates the current ratio as a complementary signal to sales growth rate. While sales growth rate provides insights into a company's potential for expansion and market competitiveness, the current ratio offers a crucial dimension by

assessing its short-term liquidity and ability to meet immediate obligations. This combined analysis ensures a more comprehensive evaluation, addressing both long-term growth potential and short-term financial health in the ever-changing landscape of investment decision-making.

Evidence suggests that firms face higher bankruptcy risk at different phases of the life cycle, with heightened risk during the introduction, growth, and decline phases, while being relatively lower during the mature stage (Akbar et al., 2019).

2.5.2. Methodology

The main objective of this study is a comparative analysis of the financial performance of 10 diverse portfolios spanning the period from 2000 to 2022.

The 9 portfolios, excluding the market portfolio used as a benchmark, are categorized into 3 groups based on a combination of the sales growth rate and the current ratio. The first group combines stocks of companies with the highest sales growth rate and the highest current ratio, the second comprises stocks of companies with the highest sales growth rate, and the third on stocks of companies with the highest current ratio. This strategic grouping serves to reveal whether the combination of these two signals is relevant in developing an effective investment strategy.

In all three groups, identical methodologies are applied to construct portfolios. A Long-Only portfolio, named Long-Top, is created by taking a long position on the top tercile of companies identified as 'Tercile 0' based on the combined ranking of the sales growth rate and current ratio. Similarly, a Long-Only portfolio on the bottom tercile of companies is formed, named Long-Bottom, with an objective to identify investment opportunities among undervalued or challenged companies. Additionally, a Long-Short portfolio is created to generate returns by exploiting differences in the performance of the two sets of investments. These portfolios are benchmarked against an equally weighted market portfolio.

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For this purpose, three rankings were created, focusing on the sales growth rate, the current ratio, and on a combination of the two parameters. The division into terciles is done annually for each of the rankings, ensuring that the portfolios are constructed based on current market conditions, enhancing the relevance of the strategies.

All portfolios adopt an equal-weighting approach, ensuring that each stock in a portfolio carries the same weight. This methodology is embraced to eliminate biases stemming from uneven capital allocations, facilitating a straightforward risk assessment. Furthermore, only sales growth rate and current ratio values greater than or equal to 0 are considered in building all portfolios.

2.5.3. Results

The graphical representation of the portfolios' accumulated returns reveals some dynamics in their performance over the sample period. Initially, all portfolios outperform the market, with the Long-Bottom Sales and Current Ratio portfolio standing out. Nevertheless, the benchmark consistently exhibits stronger overall performance, particularly in recent years.

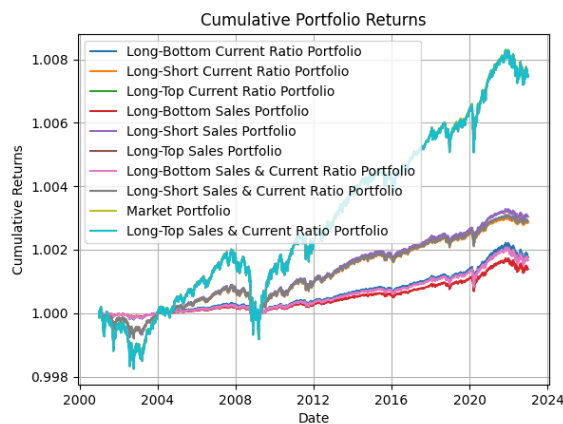


Figure 42: Portfolios' Cumulative Returns

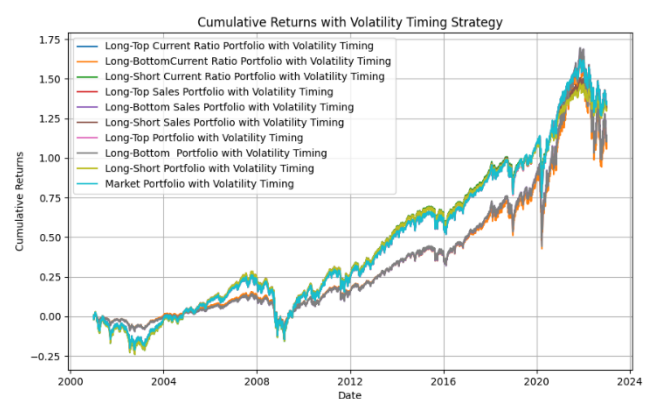


Figure 53: Portfolios' Cumulative Returns with a Volatility Timing Strategy

Notably, both the Long-Short and Long-Bottom portfolios display diminishing returns, marked by a peak followed by a significant decline around the 2007/2008 period. This trend is

associated with the housing market bubble, which, when it burst, triggered the global financial crisis of 2008.

In the initial years, none of the portfolios achieved cumulative returns surpassing 1.004, potentially influenced by economic events such as the dot-com bubble crash. In contrast, the latter half, especially around 2017/2018, witnessed positive and more substantial cumulative returns for portfolios, notably the Market Portfolio and Long-Top portfolio, linked to the Tax Cuts and Jobs Act of 2017. Also, recent years (2019/2020) experienced a decline in portfolio returns, attributed to the outbreak of the COVID-19 pandemic.

To complement the graphical analysis of these portfolios, a volatility-timing strategy was created by applying a constant leverage of 10% annualized volatility to the returns of the portfolios. This strategy, while limiting cumulative returns, exhibits a notable characteristic of achieving higher maximum cumulative returns compared to the previous approach, indicating a trade-off between short-term losses and the strategic capture of favorable market conditions.

Performance metrics are instrumental in evaluating the overall performance of an investment portfolio.

		Performance Indicators					
		Average Annualized Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis	Max Drawdown
In sample	Long-Top Sales & CR Portfolio	0.0287%	0.0050%	0.02291	-0.09152	8.20515	-0.00280
	Market Portfolio	0.0288%	0.0050%	0.02503	-0.09000	8.26734	-0.00282
	Long-Short Sales & CR Portfolio	0.0120%	0.0021%	0.02243	-0.07793	8.05673	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0048%	0.0008%	0.02293	-0.16271	9.06930	-0.00044
	Long-Top Sales Portfolio	0.0288%	0.0050%	0.02450	-0.09180	8.32141	-0.00281
	Long-Short Sales Portfolio	0.0124%	0.0022%	0.02262	-0.08126	8.18907	-0.00122
	Long-Bottom Sales Portfolio	0.0039%	0.0006%	0.02292	-0.15870	9.28426	-0.00037
	Long-Top CR Portfolio	0.0287%	0.0050%	0.02456	-0.09031	8.24690	-0.00281
	Long-Short CR Portfolio	0.0118%	0.0021%	0.02250	-0.07414	7.96206	-0.00117
	Long-Bottom CR Portfolio	0.0051%	0.0008%	0.02295	-0.17022	9.83142	-0.00048
Out Of Sample	Long-Top Sales & CR Portfolio	0.0455%	0.0047%	0.03856	-0.67465	12.65674	-0.00149
	Market Portfolio	0.0457%	0.0047%	0.02964	-0.69033	13.23384	-0.00151
	Long-Short Sales & CR Portfolio	0.0158%	0.0014%	0.04344	-0.71792	12.83809	-0.00046
	Long-Bottom Sales & CR Portfolio	0.0139%	0.0019%	0.03868	-0.57619	12.07289	-0.00057
	Long-Top Sales Portfolio	0.0456%	0.0047%	0.03004	-0.66260	12.40229	-0.00147
	Long-Short Sales Portfolio	0.0170%	0.0016%	0.04228	-0.69587	12.58713	-0.00050
	Long-Bottom Sales Portfolio	0.0116%	0.0015%	0.03856	-0.56676	11.85340	-0.00046
	Long-Top CR Portfolio	0.0455%	0.0047%	0.02872	-0.67846	12.67244	-0.00149
	Long-Short CR Portfolio	0.0155%	0.0014%	0.04447	-0.75402	13.54606	-0.00045
	Long-Bottom CR Portfolio	0.0145%	0.0020%	0.03850	-0.53224	11.29069	-0.00059
Full Sample	Long-Top Sales & CR Portfolio	0.0341%	0.0049%	0.02768	-0.25653	9.42256	-0.00280
	Market Portfolio	0.0342%	0.0049%	0.02494	-0.26140	9.63589	-0.00282
	Long-Short Sales & CR Portfolio	0.0132%	0.0019%	0.02714	-0.16970	9.52100	-0.00118
	Long-Bottom Sales & CR Portfolio	0.0077%	0.0012%	0.02772	-0.63638	23.92324	-0.00057
	Long-Top Sales Portfolio	0.0341%	0.0049%	0.02499	-0.25195	9.43088	-0.00281
	Long-Short Sales Portfolio	0.0139%	0.0020%	0.02737	-0.18365	9.45658	-0.00122
	Long-Bottom Sales Portfolio	0.0064%	0.0010%	0.02769	-0.61602	23.09241	-0.00046
	Long-Top CR Portfolio	0.0341%	0.0049%	0.02433	-0.25634	9.45474	-0.00281
	Long-Short CR Portfolio	0.0130%	0.0019%	0.02727	-0.16510	9.57061	-0.00117
	Long-Bottom CR Portfolio	0.0081%	0.0013%	0.02771	-0.58625	22.45816	-0.00059

Table 10: Portfolios' Performance Indicators Results

In the in-sample period, Long-Top portfolios stand out with the highest average annualized returns. The value of the Market portfolio is closely replicated by the Long-Top portfolio built solely based on the companies' sales growth rate. The Sharpe ratio, higher for Long-Top portfolios, suggests better risk-adjusted performance.

All portfolios display negative skewness values, indicating a higher likelihood of extreme negative returns. This conclusion is further supported by kurtosis values. These findings are consistent in the out-of-sample period, validating the attractiveness of the Long-Top portfolio based on the highest values of companies' sales growth rates for investors.

CAPM

The Long-Top portfolios maintain their position as the most promising strategy, with a beta approximately equal to 1, indicating that the portfolio tends to move in line with the benchmark. The alpha value, approximately equal to 0, suggests that the portfolio's returns are largely in line with what would be predicted by its beta. The negative t-statistic indicates that the alpha is statistically significant, implying that it is unlikely to have occurred by chance. However, the negative value obtained through the information ratio raises concerns about the risk-adjusted performance of the portfolio.

CAPM Results										
		Long-Top Sales & CR	Long-Bottom Sales & CR	Long-Short Sales & CR	Long-Top Sales	Long-Bottom Sales	Long-Short Sales	Long-Top CR	Long-Bottom CR	Long-Short CR
In-Sample	Beta	0.99917	0.14855	0.42531	1.00092	0.12542	0.43775	0.99965	0.16238	0.41863
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.36906	0.77079	-0.84009	-0.13219	0.61593	-0.63169	-0.23208	0.64066	-0.69615
	IR	-0.00601	0.01256	-0.01368	-0.00215	0.01003	-0.01029	-0.00378	0.01044	-0.01134
Out-Of-Sample	Beta	0.99451	0.38589	0.30431	0.99176	0.31888	0.33644	0.99380	0.41500	0.28940
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	0.18207	-1.66968	1.67931	0.34743	-1.58737	1.64077	0.17268	-1.63421	1.66752
	IR	0.00434	-0.03983	0.04006	0.00829	-0.03787	0.03914	0.00412	-0.03898	0.03978
Full Sample	Beta	0.99780	0.21858	0.38961	0.99822	0.18251	0.40786	0.99792	0.23692	0.38050
	Alpha	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	T-Stat Alpha	-0.20292	0.09699	-0.11282	0.04920	0.08725	-0.07547	-0.13853	0.00246	-0.01382
	IR	-0.00273	0.00130	-0.00152	0.00066	0.00117	-0.00101	-0.00186	0.00003	-0.00019

Table 11: CAPM Results

3 Factors Fama-French

Relating to the Fama-French Model, The Long-Top portfolios constructed present a beta with the market approximately equal to 1, signifying that the portfolio's returns are expected to move

Group Part

together with the overall market. Different portfolios exhibit varying sensitivity to additional factors like High Minus Low (HML) and Small Minus Big (SMB).

3 Factors Fama-French Analysis Results										
		Long-Top Sales & CR Portfolio	Long-Bottom Sales & CR Portfolio	Long-Short Sales & CR Portfolio	Long-Top Sales Portfolio	Long-Bottom Sales Portfolio	Long-Short Sales Portfolio	Long-Top CR Portfolio	Long-Bottom CR Portfolio	Long-Short CR Portfolio
In-Sample	Beta_Market	0.99921384	0.14604749	0.42658318	1.00092659	0.12325010	0.43883825	0.99946035	0.15969317	0.41988359
	Beta_HML	-0.00000003	0.00000071	-0.00000037	0.00000001	0.00000063	-0.00000031	0.00000004	0.00000078	-0.00000037
	Beta_SMB	0.00000003	0.00000037	-0.00000017	-0.00000002	0.00000030	-0.00000016	0.00000005	0.00000037	-0.00000016
	Alpha	0.00000000	0.00000001	-0.00000001	0.00000000	0.00000001	0.00000000	0.00000000	0.00000001	-0.00000001
	T-Stat_Alpha	-0.40608326	0.47429421	-0.56460586	-0.10266229	0.30788302	-0.33026025	-0.37515748	0.34398428	-0.43080153
	Information_Ratio	-0.00661724	0.00772876	-0.00920041	-0.00167291	0.00501704	-0.00538168	-0.00611330	0.00560532	-0.00702003
Out-Of-Sample	Beta_Market	0.99420752	0.38451241	0.30484755	0.99122608	0.31767913	0.33677348	0.99352013	0.41314820	0.29018597
	Beta_HML	-0.00000010	-0.00000080	0.00000035	-0.00000017	-0.00000067	0.00000025	-0.00000011	-0.00000103	0.00000046
	Beta_SMB	0.00000007	0.00000026	-0.00000009	0.00000014	0.00000024	-0.00000005	0.00000007	0.00000037	-0.00000015
	Alpha	0.00000000	-0.00000014	0.00000007	0.00000001	-0.00000011	0.00000006	0.00000000	-0.00000017	0.00000009
	T-Stat_Alpha	0.23805171	-1.65286933	1.66265140	0.41154406	-1.56789758	1.62536519	0.22457080	-1.61738865	1.65024542
	Information_Ratio	0.00568050	-0.03944156	0.03967499	0.00982046	-0.03741393	0.03878525	0.00535882	-0.03859491	0.03937895
Full-Sample	Beta_Market	0.99784108	0.21864896	0.38959606	0.99831661	0.18253373	0.40789144	0.99789976	0.23714786	0.38037595
	Beta_HML	-0.00000005	-0.00000078	0.00000036	-0.00000005	-0.00000062	0.00000028	-0.00000002	-0.00000091	0.00000045
	Beta_SMB	0.00000003	0.00000081	-0.00000039	0.00000000	0.00000066	-0.00000033	0.00000004	0.00000087	-0.00000042
	Alpha	0.00000000	0.00000001	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000
	T-Stat_Alpha	-0.20249344	0.06982433	-0.08611768	0.06752326	0.05888318	-0.04531351	-0.15938848	-0.02142031	0.00779763
	Information_Ratio	-0.00272377	0.00093922	-0.00115838	0.00090826	0.00079205	-0.00060952	-0.00214395	-0.00028813	0.00010489

Table 12: Fama-French 3 Factors Results

These outcomes are substantiated through the alpha obtained for each portfolio, suggesting that the portfolio's returns align with what would be expected given its exposure to systematic risk factors. The negative t-statistic on the alpha implies that the estimated alpha is not significantly different from zero, raising questions about the portfolios generating excess returns beyond what would be expected based on their active risk exposure.

3. Data

The data consists of monthly returns of the five individual strategies: Tax Surprise, Age, ESG, Value plus Momentum, and Sales. The monthly characteristic of the data allows for a more significant number of observations in our dataset and simultaneously reduces noise in the data.

The data used for the regressions and for the risk-free rate was obtained from the Kenneth R. French Data Library. The factors in the regressions include all NASDAQ, NYSE, and AMEX firms.

An aspect worth considering is the relationship between the returns of these individual strategies. The covariance matrix displays useful information to understand the relationship

between the returns of the five individual strategies, as it displays the variance of each strategy (diagonal elements) and the covariance of each pair of individual strategies (non-diagonal elements).

	Tax Surprise	Age	ESG	Value+Mom	Sales
Tax Surprise	0.00288	-0.00134	0.00006	-0.00043	-0.00002
Age	-0.00134	0.01964	0.00184	0.00526	-0.00067
ESG	0.00006	0.00184	0.00108	0.00019	0.00029
Value+Mom	-0.00043	0.00526	0.00019	0.00304	-0.00028
Sales	-0.00002	-0.00067	0.00029	-0.00028	0.01537

Table 13: Signals' Covariance Matrix

From this covariance matrix, it is possible to understand, by looking at the diagonal elements, that the strategy with the highest variance, therefore the strategy with the most volatile returns, is the Age strategy, with a variance of 0.01964, followed by the Sales strategy (variance of 0.01537). On the opposite side, the less volatile strategy is the ESG strategy with a variance of 0.00108.

Considering the covariances between the strategies, the main takeaway is the evident positive relation of the ESG strategy with all the other strategies, which when paired with the fact that this is the least volatile strategy, leads to the belief that this strategy will offer diversification benefits when building the combined strategy. Additionally, the negative correlation of the sales strategy with all the other strategies, expecting the ESG, can also benefit the combined strategies as this strategy could act as a hedge to the other strategies, by performing well in periods where these strategies are performing poorly.

4. Methodology

The returns span from January 2003 to December 2022 and are divided into in-sample and out-of-sample periods. The in-sample period spans from January 2003 to December 2015, and the out-of-sample period from January 2016 to December 2022. Both bull and bear markets take

place during these periods, which allows for a comprehensive testing ground for the performance of our strategies.

Five different approaches were tested for the construction of the portfolios:

- A Maximum Sharpe Ratio (MSR) was employed to maximize the risk-adjusted return. This was done by calculating the optimal combination of the individual strategies that resulted in the highest Sharpe Ratio, which is the ratio of excess return to volatility. For this purpose, it adjusted the weights of each element, considering both the expected returns and the covariance among the strategies.
- A Global Minimum Volatility (GMV) strategy that aims to minimize the total strategy's risk. It found the combination of the strategies that resulted in the lowest volatility achievable, considering how these strategies covary with one another. This can be considered a very suitable approach for risk-averse investors since it aims to minimize the potential for significant fluctuations in the strategy's value.
- An Equally Weighted (EW) approach, where each individual strategy is assigned identical weights, regardless of its historical performance or risk profile. This straightforward approach assumes that all the individual strategies will contribute equally to the strategy's performance, providing an unbiased and simple diversification method.
- Two Volatility Timing strategies were tested, involving dynamically adjusting the strategy based on its historical volatility, specifically the 12-month historical volatility of the strategy. Using a 12-month period for assessing historical volatility makes it possible to capture a more comprehensive view of market fluctuations. This time frame is sufficiently extensive to mitigate abrupt fluctuations in volatility yet short enough to maintain its applicability to present market conditions. Two different volatility targets are tested: 5% and 8%. The approach begins with the MSR strategy's weights and then

scales them up or down based on how the recent historical volatility of the strategy compares to the target volatility. By doing this, it allows the strategy to respond to changing market conditions, which has the potential to reduce risk during more volatile times and take more risk when markets are more stable. After testing for both volatility targets, the one that yielded better risk-adjusted returns was kept.

The first part of our analysis focused on in-sample data. For the evaluation of the performances, metrics like annualized returns, volatility, and Sharpe Ratios were considered. The Sharpe Ratio was computed using risk-free rates obtained from the Kenneth R. French Data Library. These rates proxy for one-month Treasury Bills.

In addition, the maximum drawdown, being the largest peak-to-trough decline in the value of investment strategy, was also necessary to analyse the potential downside risk of these strategies.

To assess the characteristics of the returns and risks associated with these strategies, both the Capital Asset Pricing Model (CAPM), used to estimate the market risk exposure, and the Fama-French 5-Factor Model plus Momentum that considers size, value, profitability, investment, and momentum factors were used. Through these regressions, variables like alphas, betas, tracking errors, and information ratios were obtained and analysed to have a comprehensive view of the strategies.

For comparison purposes, a proxy of the NASDAQ Composite Index was built by value-weighting the returns based on the market capitalization, and a volatility timing strategy was built from it. A traditional 60/40 portfolio that invested 60% in the market portfolio and 40% in the risk-free rate was produced to compare our strategy further. The choice for this method is due to it being generally acknowledged for its well-balanced strategy, that attracts a diverse group of investors who seek both growth and risk management. Afterwards, to provide a

comparison of our strategies against a more equity-heavy, growth-oriented investment method, an 80/20 portfolio was also developed.

To validate the robustness of our approaches, the analysis was then extended to out-of-sample data. This section was fundamental to assess the predictive power and whether the strategies were efficient in different market conditions, not taken into account in the in-sample period.

Lastly, to perform an assessment of the portfolio efficiencies, the efficient frontier and the capital market line were plotted to determine the tangency portfolio. Firstly, to calculate and plot the efficient frontier, the full-sample covariance matrix of the strategies returns was used. This involved an assessment of the several combinations of strategies to determine their expected returns and volatilities. For the capital market line (CML), this line departs from the risk-free rate (which in this case since we are dealing with excess returns is set to zero) and is tangent to the efficient frontier. This line represents the portfolios that optimally balance risk and returns. The intersection between the CML and the efficient frontier, allowed the Tangency Portfolio to be obtained. This point is represented in the graph below and showcases where it is possible to achieve the best risk-adjusted returns given our set of strategies.

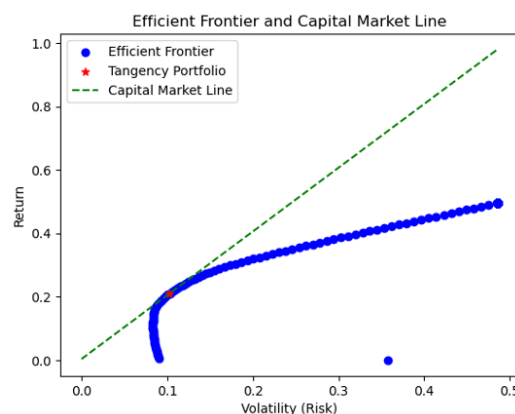


Figure 64: Efficient Frontier and Capital Market line

5. In-Sample Results

In this chapter, our focus shifts from the theoretical foundations and methodological framework, as discussed in Chapter 4, to an analysis of sample results derived from our

designed investment strategies. This section serves as the empirical core of our study, providing a comprehensive analysis of the performance of the strategies within the designated in-sample period, between 2003 and 2015. The following sections of this chapter will present the results achieved from the developed strategies, exploring performance metrics, and extrapolating valuable information, seeking to validate the effectiveness of our strategies.

5.1. Performance Indicators

Portfolios Performance Indicators Results				
		Annualized Monthly Returns (%)	Annualized Volatility (%)	Sharpe Ratio
In-Sample	Max SR	25.212905	14.412242	1.749409
	GMV	4.719625	8.461748	0.557760
	EW	-11.027876	13.173613	-0.837118
	Vol Timing 8% target	13.748371	8.668245	1.586062
	Market	17.914859	15.742359	1.138003
	Market Vol Timing	8.953669	8.659352	1.033988
	60-40	11.250454	9.426996	1.193429
	80-20	14.582656	12.584036	1.158822

Table 14: In-Sample Portfolios' & Comparison Strategies Performance Indicators Results

The four strategies - namely, the Maximum Sharpe Ratio strategy, the Minimum Volatility strategy, the Equally Weighted strategy, and the innovative Volatility Timing strategy with a target of 8% - will be subject to scrutiny of their Annualized Average Returns, Annualized Standard Deviations, and Sharpe ratios. These metrics constitute the performance barometers of our strategy, guiding our assessment of both returns and risk.

Looking at the results presented, it was developed a comprehensive exploration of performance within the Maximum Sharpe Ratio (MSR) strategy sample. Strategy results present a narrative of financial effectiveness, characterized by an average annualized return of 25.2%. This return is harmoniously associated with a moderate annualized standard deviation of 14.4%, reflecting a balance between risk and reward. Furthermore, the Sharpe Ratio of 1.75 underlines the strategy's ability to outperform a risk-free investment, highlighting its ability to generate returns while efficiently managing risk over the specified period.

In relation to the Global Minimum Variance (GMV), we can observe that this strategy is characterized by an average annualized return of 4.7%. Furthermore, the GMV demonstrates a deliberate emphasis on reducing risk, as evidenced by a low annualized standard deviation of 8.5%. The GMV strategy stands out for its commitment to minimizing variance and, in turn, achieving a notable reduction in volatility. The Sharpe Ratio of 0.56, highlights the compromise between risk and return, indicating that this strategy offers positive risk-adjusted performance, particularly appealing to investors who prioritize stability and risk mitigation.

Over the in-sample period, the Equally Weighted strategy emerges with a challenging scenario, characterized by a notable average annualized return of -11%. This negative return is accompanied by a moderate annualized standard deviation of 13.1%. The resulting Sharpe Ratio of -0.84, however, paints a more complex picture, signifying negative risk-adjusted performance during this period.

Finally, the analysis of the Volatility Timing strategy operating with an 8% volatility target reveals a [notable outcome](#). The period in focus paints a successful picture, characterized by a remarkable average annualized return of 13.7%, in line with an annualized standard deviation of 8.7% that closely follows the predetermined volatility threshold. The resulting Sharpe Ratio of 1.58 signifies a successful synthesis of effective risk management and profitable market navigation. Thus, it emerges as a promising strategic paradigm for investors seeking a balance between risk mitigation and return optimization.

5.2. Cumulative Returns and Drawdowns

Cumulative returns reveal the evolving story of wealth accumulation over time, while drawdowns provide a clear illustration of strategy resilience during adverse market conditions. By visualizing these elements, we gain a differentiated understanding of strategy's evolution, offering insights that go beyond traditional metrics.

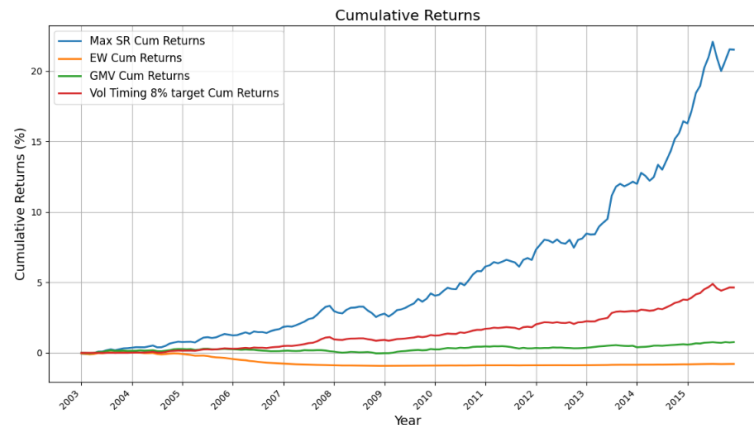


Figure 75: In-Sample Portfolios' Cumulative Returns

The EW strategy, revealing a negative trend and persistently negative cumulative returns, highlights the challenges associated with an even distribution of assets.

In contrast, GMV and Volatility Timing, both of which exhibit a steady and nearly linear increase in cumulative returns. Although their returns remain below the 500% mark, their consistent upward trajectories highlight a commitment to risk mitigation and suggest potential appeal to risk-averse investors seeking stable, albeit modest, returns.

Nevertheless, it is the MSR strategy that stands out, delivering cumulative returns that exceed the 2000% mark. The non-linear nature of its growth trajectory, particularly evident in the later years of the sample period, suggests a dynamic strategy that adapts to changing market conditions. The strategy's accelerated growth rate in recent years highlights the potential benefits of pursuing an optimized risk-return profile.

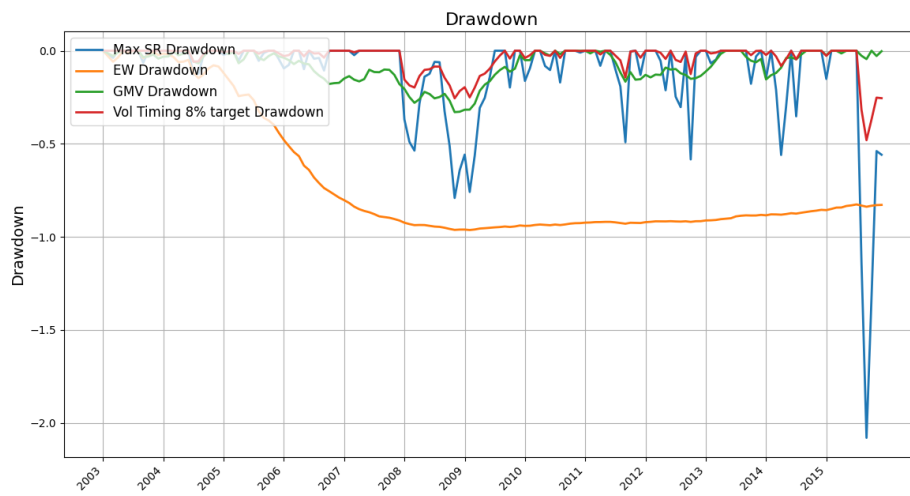


Figure 86: In-Sample Portfolios' Drawdowns

The analysis of the drawdowns of our four investment strategies reveals distinct narratives that reflect the behaviours described in our analysis of performance indicators. The GMV and Volatility Timing strategies present drawdowns around the zero mark. While its commitment to stability is clear, fluctuations in reduction behaviour introduce an element of unpredictability, reflecting our conclusions from a more uncertain performance scenario. The notable reduction spikes in 2009 and 2015 reflect the strategies' response to specific market challenges, emphasizing the need for vigilant monitoring and adjustment.

Lastly, the MSR reflects the strategy's propensity for higher returns and greater volatility. Its drawdown pattern is not linear, presenting pronounced peaks that notably exceed -2% in 2016.

5.3. CAPM Results

According to modern portfolio theory, the Capital Asset Pricing Model (CAPM) provides a theoretical framework for evaluating the risk and return of investment portfolios. Through this analysis, we seek to not only quantify the risk premium associated with each strategy, but also understand the expected returns and unique characteristics of our diversified investment approaches.

CAPM Portfolio In-Sample Results				
	Max SR	EW	GMV	Vol Timing 8% target
Alpha	0.016579	-0.012768	0.001788	0.009203
Alpha T-value	6.113802	-4.857331	1.033141	5.235657
MktRf beta	0.604875	0.488328	0.292761	0.307578
MktRf t-value	9.341792	7.780371	7.084637	7.328025
IR	0.497163	-0.394990	0.084013	0.425754
R²	0.361709	0.282166	0.245808	0.258546

Table 15: In-Sample Portfolios' CAPM Results

When looking at the results in the table, we see that the Capital Asset Pricing Model (CAPM) highlights what had already been interpreted about the MSR. With an alpha of 0.016 and a significant alpha t-value of 6.114, the MSR distinguishes itself as a consistent outlier, outperforming predicted returns with a statistical robustness that captures the attention of astute

investors. The strategy's defensive posture, evidenced by a market beta of 0.649, positions it as a robust number in the face of market changes, demonstrating resilience to volatile situations. Furthermore, the Information Ratio of 0.497 highlights its ability to consistently produce excess returns relative to the benchmark index. This dynamic performance is further nuanced by the R-squared value of 0.3617, providing insight into the intricate interplay between market dynamics and the idiosyncratic factors that influence the trajectory.

In the domain of dynamics, the GMV strategy stands out. The positive alpha of 0.0018 suggests the ability of the GMV to exceed predicted returns, but the significance portrayed by the alpha t-value of 1.033 requires measured interpretation. With a market beta of 0.29276, the GMV is positioned defensively, demonstrating resilience that transcends market volatility. While the Information Ratio of 0.084 suggests a modest ability to generate excess returns relative to its benchmark, the R-squared value of 0.2458 speaks volumes about the GMV strategy's dependence on factors beyond systematic market movements.

Regarding the EW strategy, the trajectory is marked by a pronounced negative alpha of -0.0129, a revelation that reflects a consistent underperformance compared to expected returns, given its systematic risk. The highly significant negative alpha t-value of -4.857 underscores the statistical robustness of this underperformance, requiring meticulous examination of the strategy's divergence from predicted results. Nestled with a market beta of 0.488, this strategy describes a moderately sensitive position to market fluctuations, investigating the intricacies of its volatility dynamics. This narrative is further accentuated by an Information Ratio of -0.395, casting a shadow over the ability to generate positive risk-adjusted returns. The R-squared value of 0.282 reveals the existence of influences that go beyond systematic market movements, shaping the performance scenario. Thus, the Equally Weighted strategy emerges as a diversification strategy that faces the challenges of risk-adjusted returns.

Finally, the Volatility Timing strategy emerges as a standout performer in the complex domain of investment strategies. The positive alpha, supported by a highly significant alpha t-value of 5.236, underlines a consistent ability to outperform predicted returns with statistical robustness. The market beta of 0.307 implies that this strategy is resilient to market fluctuations, reflecting a strategic orientation towards mitigating volatility. The Information Ratio of 0.426 reveals an ability to generate excess returns relative to its benchmark, affirming its ability to deliver positive risk-adjusted performance. As the R-squared value of 0.259 unravels the complexities of its performance picture, it becomes evident that the strategy's success is not just tied to systematic market movements, but rather inextricably intertwined with unique factors.

5.4. Fama-French Five Factor Model (FF5) + Momentum results

Fama-French Five Factor Model (FF5) + Momentum results					
		Max SR	EW	GMV	Vol Timing 8% target
In-Sample	Alpha	0,0172	-0,0127	0,0015	0,0092
	Alpha T-value	67,422	-48,151	0,8933	55,234
	MktRf beta	0,5124	0,4117	0,2153	0,3198
	MktRf t-value	68,737	53,659	43,057	66,169
	SMB beta	0,3986	0,3348	0,3269	0,1577
	SMB t-value	32,775	26,745	40,079	20,005
	HML beta	-0,3449	-0,3266	-0,1192	-0,1865
	HML t-value	-26,823	-24,677	-13,823	-22,380
	RMW beta	-0,3912	-0,1768	0,0127	-0,1118
	RMW t-value	-23,532	-10,332	0,1135	-10,378
	CMA beta	-0,3084	0,0367	0,1317	-0,3655
	CMA t-value	-14,802	0,1710	0,9425	-27,064
	Mom beta	0,0531	-0,0389	-0,0491	0,0881
	Mom t-value	0,8923	-0,6341	-12,296	22,840
	IR	0,5676	-0,4054	0,0752	0,4650
	R ²	0,4882	0,3511	0,3322	0,4055

Table 16: In-Sample Fama-French 5 Factors & Momentum Portfolios' Results

The Fama-French Five Factor Model (FF5) was introduced by Fama and French (2015) as an extension to the original Fama-French Three Factor Model (FF3), an asset pricing model first introduced in 1992 that added two additional risk factors: size (SMB) and value (HML), to the market factor from the traditional CAPM model. In the most recent extension, the profitability (RMW) and investment (CMA) factors were introduced. Additionally, the Momentum factor was introduced by Carhart (1997), based on the work of Jegadeesh and Titman (1993) which

showed empirical evidence supporting the idea that stocks with good performance (winners) in the recent past tend to continue to perform well in the short term and that stocks that performed poorly (losers) in past tend to continue the poor performance in the future.

Table 6 displays the strategy's performance on the FF5 + Momentum risk factors.

The MSR strategy exhibits an alpha of 0.017, the highest out of the four strategies, meaning that this is the one that generates the highest returns in excess of the risk factors. On the opposite side, the EW strategy has the worst performance, with an alpha of -0.013, signaling that this strategy underperforms the benchmark. Perhaps the most interesting remark to make from these results is not the results themselves, but rather the comparison with the CAPM results from the previous section. When comparing these results, it is possible to see that the alphas remain unchanged from the CAPM to the FF5 + Momentum, an interesting finding that can lead to the conclusion that the returns of the portfolios are primarily affected by the market risk, meaning that risk is the predominant driver of their returns and that the additional factors do not significantly affect the performance of the portfolios. Nonetheless, it is relevant to analyze the effects of these risk factors on the portfolios' performance to better understand the risk they are exposed to.

In the case of the market factor, the beta represents the portfolio's sensitivity to changes in the market excess returns but can also be interpreted as the risk the portfolio is exposed to by changes in the market conditions. The results show that all four strategies are positively related to the market (positive betas) meaning that their returns tend to move in the same direction as the market returns. In addition, all have betas lower than 1, which leads to the conclusion that their returns are less volatile than the market, a finding that may be related to the diversification process that occurred from combining five independent strategies into a unified collective strategy. Out of these strategies, the beta of the MSR is the highest, meaning it has the highest

risk exposure, and on the opposite side, the Global Minimum Variance is the least exposed to systematic risk, which is expected due to its construction. It is also worth mentioning that applying the volatility timing technique, by targeting an 8% annualized standard deviation, leads to a decrease of almost half in its risk exposure. This interpretation comes from the difference in the betas of the MSR (beta of 0.512) and the Volatility Timing (beta of 0.320).

All strategies present positive, statistically significant betas on the size (SMB) portfolio, which signifies that all four are positively exposed to the risk this factor represents. Moreover, this entails that these portfolios' returns are positively related to the returns of small-cap stocks. The strategy with the highest beta on the size factor is the MSR (0.399), which is reasonable considering that this is the most volatile portfolio and that the returns of small-cap stocks are more volatile than those of large-cap stocks.

Additionally, the portfolios present statistically significant negative betas on the value (HML) portfolio, results that lead to the conclusion that the portfolios are negatively exposed to this risk and that their returns are more related to the returns of growth stocks, stocks of companies with low book-to-market ratios. The MSR is the one with the most significant exposure to the value factor, with a beta of -0.345, meaning that this strategy is the one that best resembles a growth portfolio.

Moreover, the betas on the profitability (RMW), investment (CMA), and Momentum (Mom) factors do not have a significant effect on the returns of all portfolios. Only the MSR has a statistically significant beta on the profitability factor, a negative beta that signifies that this is more exposed to the returns of stocks of companies with weak operating profitability than those of companies with robust operating profitability. The Volatility Timing strategy is the only with a statistically significant beta on the investment factor, a negative beta that leads to the belief that these returns are more exposed to the returns of stocks of companies with aggressive

investment policies than those of companies with more conservative investment policies. Finally, the effect of momentum on portfolio returns is negligible for all portfolios.

On a final note, the Information Ratio (IR) measures the portfolio's risk-adjusted performance, and the results show that, as expected, the MSR has the best risk-adjusted performance (highest IR: 0.497), and the Equally Weighted strategy has the worst risk-adjusted performance (lowest IR: -0.395), similar findings to those highlights in the analysis of the CAPM results. Nonetheless, it is worth mentioning that despite similar conclusions, the risk-adjusted performance of all strategies, except the Volatility Timing, increased from considering the exposure to the additional risk factor. This is an interesting finding that leads to the conclusion that, although the returns of these portfolios are mainly exposed to the market risk, the exposure to these additional factors has a positive contribute to the portfolios' risk-adjusted performance, particularly the positive exposure to the size factor.

5.5. Comparison Strategies

To enrich the analysis, the performance of the strategy's portfolios, especially the MSR portfolio, are compared with that of other popular asset allocations.

The in-sample strategy's performance indicators results displayed in section 4.1, show that the market portfolio (proxy of the Nasdaq Composite index) generates annualized monthly returns of 17.915%, with annualized volatility of 15.742%, resulting in a Sharpe Ratio of 1.138. From comparing its performance with that of the MSR, the conclusion can be made that the best-performing strategy outperforms the market, both with better absolute and risk-adjusted performance, with higher results, lower volatility, and higher Sharpe Ratio.

The market Volatility Timing (market VT for simplification) serves as a fair comparison to the strategy's Volatility Timing (strategy VT) based on the returns of the MSR. These results show that the strategy VT generates higher returns .13.748% against 8.954% of the market VT), with

slightly higher volatility .8.668% against 8.659% of the market VT portfolio), which results in a significantly higher Sharpe Ratio .1.586 against 1.034 of the market VT).

Moreover, these results also depict the performance of the 60-40 and 80-20 portfolios. The 60-40 portfolio is expected to generate lower returns, in absolute terms, while also generating lower volatility than the market portfolio because investing in a proportion of the overall weighted of the portfolio in the risk-free asset will lead to a decrease in both returns and their standard deviation. The same is true for the 80-20 portfolio, but on a lower scale considering that a lower weight is given to the risk-free asset. These performance results match the expectations, the 60-40 portfolio generated lower returns with lower volatility, but with better risk-adjusted performance (Sharpe Ratio of 1.193 against 1.138 of the market portfolio), and the 80-20 portfolio also generated lower returns with lower volatility, when compared with the market portfolio, but higher than those of the 60-40 portfolio, and with a higher risk-adjusted performance than that of the market portfolio but lower than that of the 60-40 portfolio. The most interesting remark is then the fact that, despite generating the lowest returns out of these three portfolios, the 60-40 manages to have the best risk-adjusted performance. Nonetheless, none of these portfolios could achieve a Sharpe Ratio as high as the MSR portfolio.

The main takeaway from this performance comparison is that the MSR, the core strategy portfolio, is undoubtedly the best-performing portfolio out of all portfolios analyzed in the in-sample period.

6. Out-of-Sample Results

In the realm of quantitative investment strategy development, the transition from in-sample to out-of-sample analysis represents a crucial step in validating the robustness and applicability of our strategies. While in-sample analysis provides initial insights and helps in fine-tuning the strategy parameters, it inherently carries the risk of overfitting to a specific dataset.

Despite our main strategies yielding promising results with combined portfolios showing optimistic performance characteristics in terms of annualized monthly returns, volatility, and Sharpe ratios, these strategies need to be validated under different market conditions of the initial strategy development process. Therefore our 4 main strategies (Maximum Sharpe Ratio, Equally Weighted, Global Minimum Volatility and MSR with volatility timing) have been decided to be back tested for an out-sample period from Jan-2016 till Dec-2022 to finally ascertain their reliability and sustainability.

6.1. Performance Indicators

The Maximum Sharpe Ratio, Global Minimum Volatility, Equally Weighted, and Volatility Timing strategies developed in-sample are reconstructed using the out-of-sample returns applying the same portfolio construction techniques detailed in our in-sample analysis section.

After the strategies are computed for the out-sample data, three main performance metrics are computed to establish a comparison between in and out-sample analysis and analyse the robustness of the strategies constructed. For our main-performing strategy in in-sample, the MSR, the validation is positive. The strategy which showed a high annualized return of 25.21% and a Sharpe ratio of 1.75 in-sample, demonstrated a lower yet impressive return of 17.42% but also a lower volatility of 10.1% compared to 14.41% in-sample, conferring it an impressive Sharpe ratio of 1.72 out-of-sample. This slight dip in performance but the maintenance of a high Sharpe ratio suggests robustness, indicating that the strategy's success is not just a product of specific historical conditions but can adapt to new market scenarios. Our second-best strategy, Volatility timing applied to MSR also performs consistently in out-sample data with a positive Sharpe Ratio of 1.24, though slightly reduced from in-sample of 1.59 due to minor

losses in performance on annualized returns, decaying from 13.75% to 11.89% and an increase in annualized volatility from 8.67% to 9.58%.

Comparison Strategies Performance Indicators				
		Annualized Returns (%)	Annualized Volatility (%)	Sharpe Ratio
In-sample	Max SR	25.21	14.41	1.75
	GMV	4.719625	8.46	0.56
	EW	-11.03	13.17	-0.84
	Vol Timing 8% target	13.75	8.67	1.59
Out-sample	Max SR	17.42	10.1	1.72
	GMV	4.88	8.59	0.57
	EW	4.77	19.64	0.24
	Vol Timing 8% target	11.89	9.58	1.24

Table 17: Comparison Strategies Performance Indicators Results

6.2. Out-Sample CAPM RegressionCAPM Returns

The comparative analysis of in-sample and out-of-sample performance using the Capital Asset Pricing Model (CAPM) regression results provides valuable insights into the robustness and consistency of the investment strategies across different market periods and help understand how it continuously performs against the market benchmark. In this section it was tested the performance of our 4 main strategies against market excess returns.

Portfolio's CAPM Out-of-Sample Results					
		Max SR	EW	GMV	Vol Timing 8% target
Out-of-Sample	Alpha	0.010498	-0.001604	0.000511	0.006317
	Alpha T-value	4.247374	-0.284243	0.251355	2.586859
	MktRf beta	0.396419	0.550099	0.350276	0.35408
	MktRf t-value	7.916894	4.81248	8.506348	7.156828
	IR	0.476377	-0.03188	0.028191	0.290137
	R^2	0.436236	0.22235	0.471824	0.387386

Table 18: Out-Of-Sample Portfolios' CAPM Results

Overall, it was observed robustness and consistency in the results obtained with MSR, GMV and Volatility Timing strategies continuing to outperform the model and generating positive alphas and Equally Weighted still falling short to the CAPM benchmark. Alpha values in the

out-sample are lower across all strategies, suggesting a reduced ability to outperform (or underperform) the market. MSR and Volatility Timing strategies fell slightly in out-sample analysis when compared to in-sample analysis. In the out-sample, the Alpha values are lower across all strategies, suggesting a reduced ability to beat the market.

T-values for all strategies fell considerably, especially for EW, indicating a loss of statistical significance. Our two best performing strategies MSR and Volatility Timing t-values fell from 6.11 and 5.23 in in-sample to 4.24 and 2.58. Nevertheless, they still hold their statistical significance comfortably corroborating their reliability to generating excess returns against the benchmark even outside the sample. Moreover, GMV T-value registered an even lower result in out-sample setting it further away from statistical significance.

Investigating the beta values, we observe that for MSR the beta decreases from and 0.6 in-sample beta to 0.4 which is associated with the strategy becoming less sensitive to market movements in the out-sample and a shift towards a non-cyclical stance compared to the in-sample period. On other hand GMV and Vol Timing betas slightly increase from 0.3 to 0.35 and 0.31 to 0.35 respectively, which despite accounting for a move towards more cyclical behavior, the overall low beta still indicates a relatively defensive positioning. Lastly EW slightly increased in out-sample analysis, reinforcing the strategy position towards a more cyclical approach, and increasing the strategy's risk profile.

Lastly, it is recorded an increase in R^2 in all strategies expect for once again EW, which might indicate a greater alignment with market trends, despite the lower beta.

6.3. Fama-French Five Factor Model (FF5) + Momentum results

Analyzing the performance of investment strategies using the Fama-French Five Factor (FF5) plus momentum (Mom) model, we compare in-sample and out-sample results to check for strategies robustness and consistency when comparing once again to different market

benchmarks in and out of sample. This model expands on the CAPM by including factors like size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (Mom), providing a more comprehensive view of the strategies' performance against market excess returns.

FF6 Comparisson in- and out-of-sample				
		Alpha	T-value	IR
In-sample	Max SR	0,0172	6.7422	0,5676
	EW	-0,0127	-4.8151	-0,4054
	GMV	0,0015	0,8933	0,0752
	Vol Timing 8% target	0,0092	5.5234	0,465
Out-of-sample	Max SR	0.008938	3.540230	0.410969
	EW	0.000267	0.046236	0.005367
	GMV	-0.000981	-0.481662	-0.055914
	Vol Timing 8% target	0.005003	1.977238	0.229528

Table 18: In and Out-Of-Sample Portfolios' FF6 Results Comparison

Best in-sample performing strategies MSR, and Volatility Timing strategies continue to generate positive alphas in the out-sample analysis, albeit at reduced levels compared to in-sample. This suggests a continued ability to outperform the benchmark, though with diminished efficacy. Specifically, the MSR strategy's alpha decreased from 0.0172 in the in-sample to 0.0089 in the out-of-sample, while the Volatility Timing strategy saw a reduction from 0.0091 to 0.005. Despite this decline, the fact that both strategies continue to generate positive alpha in the out-of-sample period suggests their sustained ability to outperform the benchmark, although with less potency than in the in-sample period. EW shows a marginal positive alpha in the out-sample, a notable shift from its in-sample underperformance. This change, however small, indicates some improvement in its performance relative to the benchmark. While GMV exhibits a negative alpha in the out-sample, contrasting with its positive in-sample alpha, suggesting a decline in its ability to generate excess returns.

In terms of effectiveness, as measured by the Information Ratio, both the MSR and Volatility Timing strategies demonstrated reduced, yet still positive IRs in the out-of-sample period, MSR declining from 0.57 to 0.41, and Volatility Timing from 0.47 to 0.23. This indicates their continued efficacy despite the reduction. However, the EW and GMV strategies showed less favorable IR results, with EW displaying a marginal positive IR and GMV a negative one in the out-of-sample period.

As for the R^2 values, which indicate the alignment with market trends, there was a slight variation across strategies, with GMV notably increasing its R^2 value in the out-of-sample period, indicating a stronger alignment with market trends despite its lower beta.

In conclusion, the FF5 + Mom model analysis reveals that the MSR and Volatility Timing strategies maintain a degree of robustness and consistency in outperforming the market benchmark, while the EW strategy shows a marginal improvement and the GMV strategy exhibits a decline in performance.

To conclude, the out-of-sample analysis suggests that the Maximum Sharpe Ratio and Volatility Timing strategies demonstrate robustness and adaptability, outperforming the market and showing their potential reliability for real-market application.

6.4. Comparison Strategies

In an effort to validate and demonstrate that our strategies are a reliable alternative to the most recognized industry strategies, we establish a comparison here on performance of our main strategies against the longing market, timing the volatility on the market 60-40 portfolio and 80-20 portfolio.

Comparison Strategies Performance Indicators				
		Annualized Returns (%)	Annualized Volatility (%)	Sharpe Ratio
Out-sample	Max SR	17.420	10.100	1.720
	GMV	4.880	8.590	0.570
	EW	4.770	19.640	0.240
	Vol Timing 8% target	11.890	9.580	1.240
	Market	23.417	19.434	1.205
	Market Vol Timing	11.082	9.521	1.164
	60-40	14.426	11.649	1.238
	80-20	18.922	15.541	1.218

Table 20: Out-Of-Sample Portfolios' Performance Indicators Results

Our best performing strategies, MSR, and Vol timing at 8% target both outperform and beat the testes market portfolios for the out-sample data, recording 1.72 and 1.24 Sharpe ratios values against 1.2, 1.16, 1.24 and 1.22 values achieved by longing market, timing the volatility on the market 60-40 portfolio and 80-20 portfolio. On the other hand, GMV and EW strategies still underperform by a long margin when compared to industry strategies.

7. Limitations

There are a couple of potential shortcomings regarding the broad applicability of the empirical analysis conducted in this paper. The original data set is restricted to securities traded on the NASDAQ Stock Exchange encompassing approximately 3,908 listed companies (NASDAQ, 2023).

A significant limitation pertains to the underlying data sources employed. To capture information of such a wide array of signals a dataset is created through the integration of well-established databases, namely Compustat, CRSP, and Refinitiv. While these sources are recognized for their comprehensive financial and market data, it is important to acknowledge that such integration may introduce potential biases or data quality issues that could impact the robustness and generalizability of the study's conclusions.

Moreover, the availability of crucial data required for constructing individual investment strategies is constrained by specific timeframes and the subset of companies covered. The total of companies used in individual strategies are respectively, 1825 for the ESG based portfolio, 2774 for the Tax-Surprise Signal, 3323 in the Value and Momentum strategy, 1825 for the Age based strategy and finally 2379 in the Sales Signal. This variance in sample sizes could also negatively affect the representativeness of the findings.

The ranking methodology employed in the individual strategies also varies, with some portfolios adopting a decile-based approach while others relying on a tercile-based method. This diversity in ranking methodologies results in distinct levels of signal concentration within the individual portfolios.

All the individual portfolios involve monthly rebalancing, which implies that investors would need to frequently adjust their allocation across different signals each month. This high frequency of trading is likely to expose investors to substantial transaction costs, potentially rendering the real-world application of these strategies. The potential solutions to mitigate this issue involve reducing the frequency of transactions and incorporating predictive models that anticipate signal significant changes.

8. Conclusion

In the group segment of this field-lab, individual strategies were integrated into five distinct approaches with the aim of achieving the most optimal strategies and comparing its performance to the most popular methods of allocation.

The evaluation of the portfolio strategies extended across various performance indicators, such as annualized returns, annualized volatility, Sharpe Ratios, drawdowns and CAPM and FF5 + Momentum model alphas.

The Maximum Sharpe Ratio strategy stands out as a top performer, showcasing stable and linear increases in cumulative returns and an impressive balance between risk and returns with a noteworthy Sharpe Ratio of 1.75 that surpasses all benchmark allocations and consistent positive significant alphas demonstrating its capability of providing excess returns. The Global Minimum Variance strategy excels in risk reduction, making it particularly appealing to risk-averse investors committed to minimizing volatility. However, it is crucial to note that this strategy's Sharpe Ratio (.056) is significantly lower than all the popular benchmark allocations and exhibits very little positive significant alphas.

The naïve allocation of the Equally Weighted strategy is by far the worst performance facing challenges with persistent negative returns and suboptimal risk-adjusted performance exhibiting a negative Sharpe Ratio of -0.84, the longest drawdown and significant negative alphas.

Finally, the Volatility Timing strategy, with a disciplined 8% volatility target emerges as the second-best, showcasing a higher Sharpe Ratio than all the benchmark strategies of 1.58 exhibiting stable and linear increases in cumulative returns and slightly positive significant alphas showcasing its capacity to deliver returns beyond what is explained by the market.

References

- Afgani, E., Rivanda, A., Purbayati, R., Marzuki, M. 2023. "The Effect of Liquidity, Leverage, Operating Capacity, Profitability, and Sales Growth as Predictors of Financial Distress: Property, Real Estate, and Construction Services Companies listed on the IDX. *Journal Integration of Management Studies*, Volume 1, 13-21.
- Akbar, A., Akbar, M., Tang, W., Qureshi, M. 2019. "Is Bankruptcy Risk Tied to Corporate Life-Cycle?". *Sustainability*, Volume 11 .678., 1-22.
- Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen. 2013.. "Value and Momentum Everywhere.". *The Journal of Finance*, 68 .3., 929-985.
- Bae, Sung C., Kim, Dongnyoung. 2003.. "The Effect of R&D Investments on Market Value of Firms: Evidence from the U.S., Germany, and Japan.". *Multinational Business Review*, 11 .3., 51–76.
- Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance.". *The Journal of Finance*, 52 .1., 57–82.
- Center for Research in Security Prices (CRSP), 2000-2022. CRSP US Stock Databases. The University of Chicago Booth School of Business. Available at: <https://wrds-www.wharton.upenn.edu/pages/get-data/center-research-security-prices-crsp/annual-update/stock-version-2/monthly-stock-file/>
- Chambers, Dennis, Jennings, Ross, Thompson, Robert B. 2002. "Excess Returns to R&D-Intensive Firms.". *Review of Accounting Studies*, 7, 133–158.
- De, I., and M. R. Clayman. 2015.. "The Benefits of Socially Responsible Investing: An Active Manager's Perspective.". *Journal of Investing*, 24.4., 49–72.

Deutsche Bank Research. November 2021. "ESG Survey – What corporates and investors think". Accessed December 9. https://www.dbresearch.com/PROD/RPS_EN-PROD/PROD0000000000520951/ESG_Survey_%E2%80%93_What_corporates_and_investors_think.pdf?undefined&reload=eBjyushDWw1/K6qyIW3pkzcyHOZCazhgcvJhqP7Nkhe4r8wI3XDD2HQv~khtEC5k

Elviana, E., Ali, H. 2021. "Determination of Financial Distress and Stock Prices: The Effect of Financial Performance and Sales Growth. Financial Management Review Literature.". Dinasti International Journal of Economics, Finance and Accounting, Volume 3 .3., 241-252.

Fama, Eugene F., French, Kenneth R. 1992. "The Cross-Section of Expected Stock Returns.". The Journal of Finance, 47 .2., 427-465.

Fama, Eugene F., French, Kenneth R. 2015. "A Five-Factor Asset Pricing Model.". Journal of Financial Economics, 116 .1., 1–22.

Fama, E.F., and French, K.R., [2000-2022]. Fama-French Research Portfolios and Factors. Available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Giarto, R., Fachrurrozie. 2020.. "The Effect of Leverage, Sales Growth, Cash Flow on Financial Distress with Corporate Governance as a Moderating Variable". Accounting Analysis Journal, 9.1., 15-21.

Graham, Benjamin, and David L. Dodd. 1934.. "Security Analysis."

House, C., Benefield, E. 1995. "The Impact of Sales and Income Growth on Profitability and Market Value Measures in Actual and Simulated Industries." Developments in Business Simulation & Experiential Exercises, Volume 22, 56-62.

- Jegadeesh, Narasimhan, Titman, Sheridan. 1993.. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.". *The Journal of Finance*, 48 .1., 65–91.
- Kipliyah, M., Hakimian. 2021.. "The Effect of Sales Growth, DPR and ROE on the Value of Food and Beverage Industry Sub-Sector Companies Listed on the IDX 2014-2019 Period.". *International Journal of Innovative Science and Research Technology*, Volume 6 .2., 1005-1010.
- Liviani, R., Rachman, Y. 2021. "The influence of leverage, sales growth, and dividend policy on company value". *International Journal of Financial, Accounting, and Management*, Volume 3 .2., 165-178.
- Loderer, Claudio F., Waelchli, Urs. 2010.. "Firm Age and Performance." *SSRN Electronic Journal*, 1, 1–52.
- Morgan Stanley Institute for Sustainable Investing. 2023.. "Sustainable Reality: Sustainable Funds Return to Outperformance in First Half of 2023".
- Pramesti, N., Yasa, P., Ningsih, N. 2021. "The Effect of Capital Structure and Sales Growth on Company Profitability and Value in the Cosmetics Manufacturing and Household Needs Manufacturing Companies.". *Jurnal Ekonomi dan Bisnis Jagaditha*, Volume 8 .2., 187-193.
- Rachmawati, R., Sherlita, E. 2021. "Effect of Sales Growth, Firm Size, Profitability on Earning Per Share" *Turkish Journal of Computer and Mathematics Education*, Volume 12 .8., 675-680.
- Ramezani, A., Soenen, L., Jung, A. 2002. "Growth, Corporate Profitability, and Value Creation." *Financial Analysts Journal*, Volume 58 .6., 56-67.

Sharpe, William F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance*, 19 .3., 425-442.

Schmidt, Peter S, Urs von Arx, Andreas Schrimpf, Alexander F Wagner. 2015.. "On the construction of common size, value and momentum factors in international stock markets: A guide with applications". Working Paper, Zurich: University of Zurich.

Tamplin, T. 2023. "Are You Retirement Ready?"

<https://www.financestrategists.com/wealth-management/financial-statements/sales/>

VanderPal, Geoffrey F. 2015. "Impact of R&D expenses and corporate financial performance." *Journal of Accounting and Finance*, 15 .7., 135-149.

Varaiya, N., Roger, A., Weeks, D. 1987. "The Relationship between Growth, Profitability, and Firm Value." *Strategic Management Journal*, Volume 8.5., 487-497.

Yuliastari, M., Najmundi, Dewi, M. 2021. "The Influence of Financial Ratios and Macroeconomic Indicators in Predicting Financial Distress. Empirical Study in the Consumer Goods Sector Companies." *International Sustainable Competitiveness Advantage*, 207-217.

Appendix

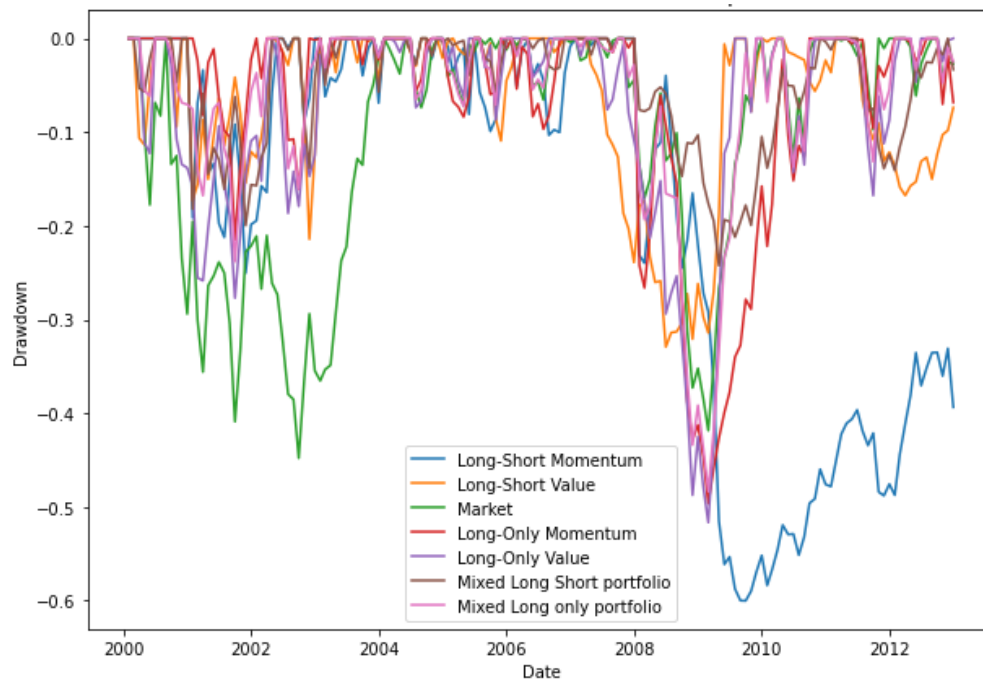


Exhibit 1: Maximum Drawdown of the Portfolios In-Sample

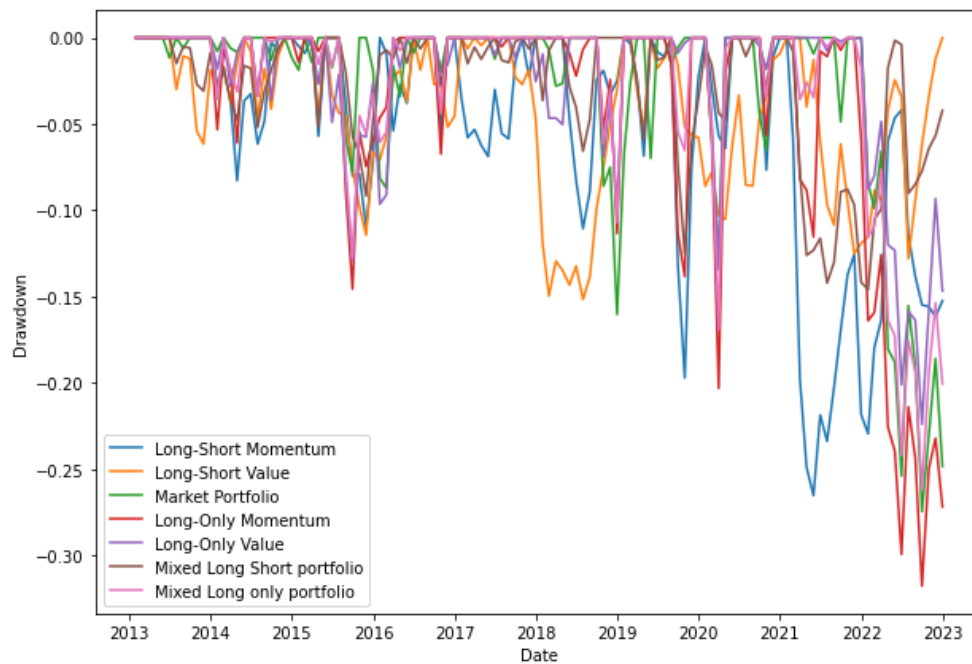


Exhibit 2: Maximum Drawdown of Portfolios Out-of-Sample

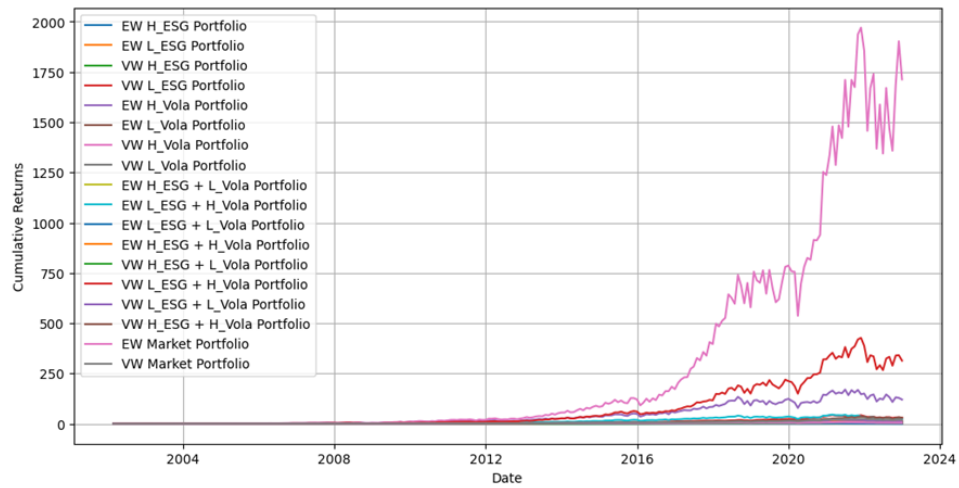


Exhibit 3: Cumulative Returns of all Portfolios in the In-Sample period

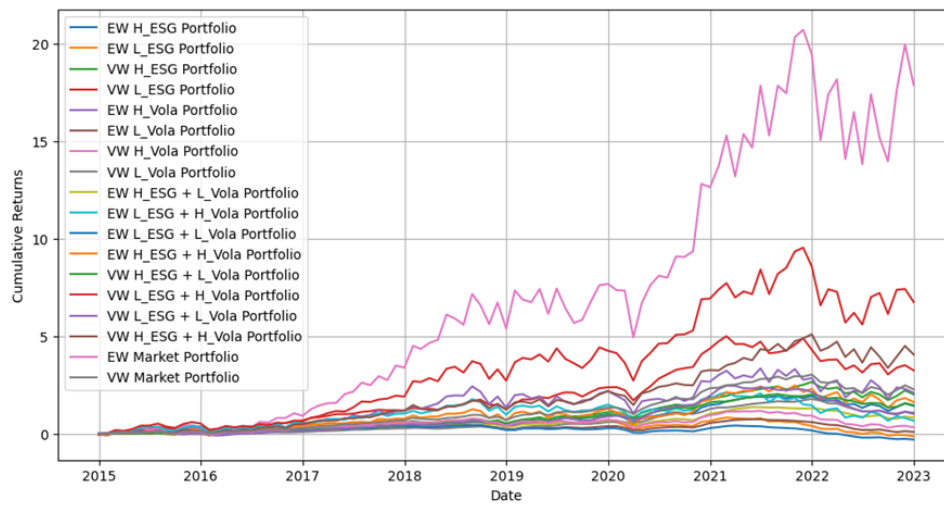


Exhibit 4: Cumulative Returns of all portfolios out-of-sample

Portfolio	Period	Annualized Return	Annualized Volatility	Sharpe Ratio
EW H_ESG	Full-Sample	12.57%	17.28%	0.727
	In-Sample	11.31%	19.58%	0.577
	Out-Sample	12.51%	17.39%	0.72
EW L_ESG	Full-Sample	11.78%	19.84%	0.594
	In-Sample	9.99%	21.62%	0.462
	Out-Sample	-0.10%	18.86%	-0.005
VW H_ESG	Full-Sample	14.52%	17.62%	0.824
	In-Sample	13.27%	20.52%	0.647
	Out-Sample	15.11%	16.69%	0.905
VW L_ESG	Full-Sample	20.48%	19.83%	1.033
	In-Sample	18.89%	21.33%	0.886
	Out-Sample	20.27%	21.21%	0.956
EW H_Vola	Full-Sample	33.81%	42.12%	0.803
	In-Sample	32.84%	44.12%	0.744
	Out-Sample	22.70%	41.95%	0.541
EW L_Vola	Full-Sample	7.75%	13.33%	0.581
	In-Sample	7.26%	13.84%	0.524
	Out-Sample	1.68%	11.47%	0.147
VW H_Vola	Full-Sample	48.14%	44.00%	1.094
	In-Sample	46.58%	45.91%	1.014
	Out-Sample	47.17%	46.03%	1.025
VW L_Vola	Full-Sample	12.79%	13.27%	0.964
	In-Sample	12.44%	14.22%	0.875
	Out-Sample	9.55%	10.35%	0.923
EW H_ESG + L_Vola	Full-Sample	9.82%	12.67%	0.775
	In-Sample	8.66%	13.68%	0.633
	Out-Sample	8.11%	11.45%	0.708
EW L_ESG + L_Vola	Full-Sample	4.73%	13.52%	0.35
	In-Sample	3.79%	14.78%	0.257
	Out-Sample	-3.72%	12.50%	-0.298
VW H_ESG + L_Vola	Full-Sample	11.66%	12.92%	0.903
	In-Sample	10.68%	14.55%	0.734
	Out-Sample	11.71%	10.95%	1.07
VW L_ESG + L_Vola	Full-Sample	14.04%	13.95%	1.007
	In-Sample	13.22%	15.83%	0.835
	Out-Sample	9.73%	14.88%	0.654
EW L_ESG + H_Vola	Full-Sample	23.43%	32.52%	0.72
	In-Sample	21.22%	33.88%	0.626
	Out-Sample	11.70%	33.05%	0.354
EW H_ESG + H_Vola	Full-Sample	19.60%	32.47%	0.604
	In-Sample	18.17%	34.25%	0.531
	Out-Sample	17.12%	32.29%	0.53
VW L_ESG + H_Vola	Full-Sample	34.02%	34.07%	0.998
	In-Sample	33.71%	34.48%	0.978
	Out-Sample	31.91%	35.95%	0.888
VW H_ESG + H_Vola	Full-Sample	22.90%	29.65%	0.772
	In-Sample	21.38%	31.40%	0.681
	Out-Sample	24.14%	28.29%	0.853
EW Market	Full-Sample	11.29%	17.84%	0.633
	In-Sample	9.98%	18.54%	0.538
	Out-Sample	5.08%	18.08%	0.281
VW Market	Full-Sample	17.30%	16.46%	1.051
	In-Sample	16.20%	17.36%	0.933
	Out-Sample	16.12%	16.62%	0.97

Exhibit 5: Performance Statistics of all Portfolios

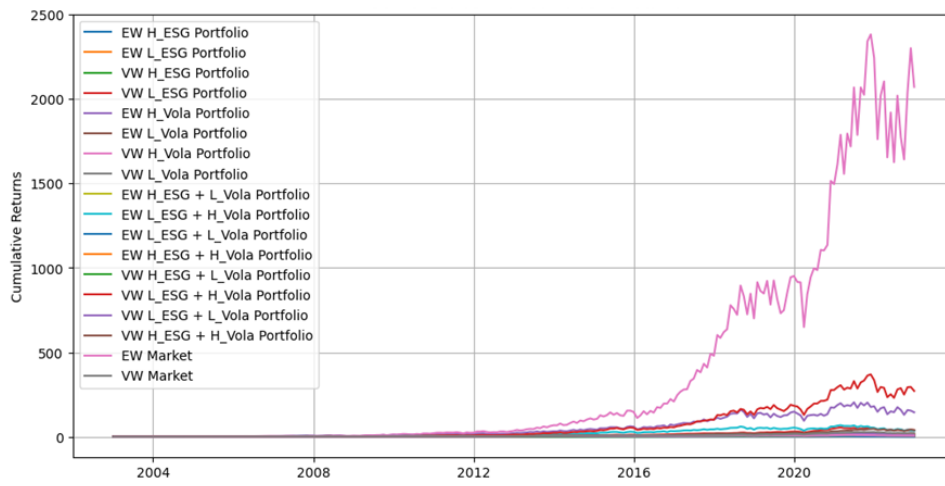


Exhibit 6: Cumulative Returns of all Portfolios in the Full-Sample period

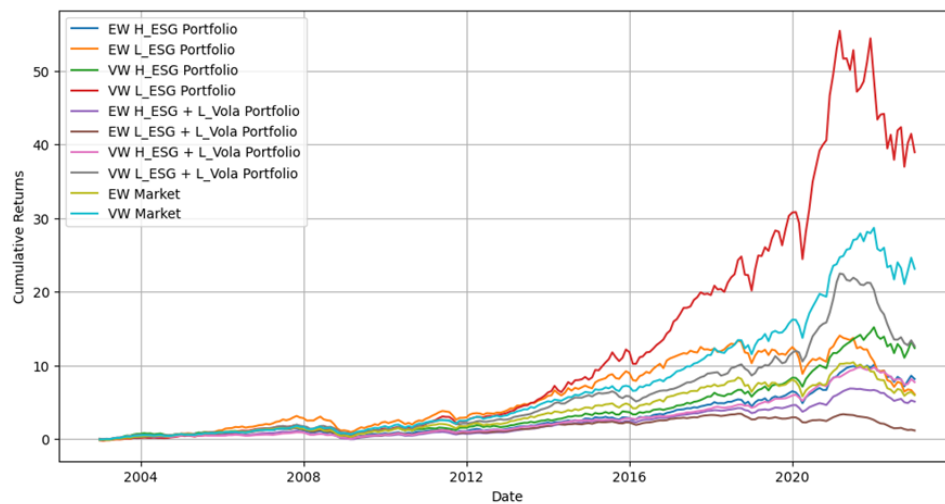


Exhibit 7: Cumulative Returns of the most relevant portfolios in the Full-Sample period

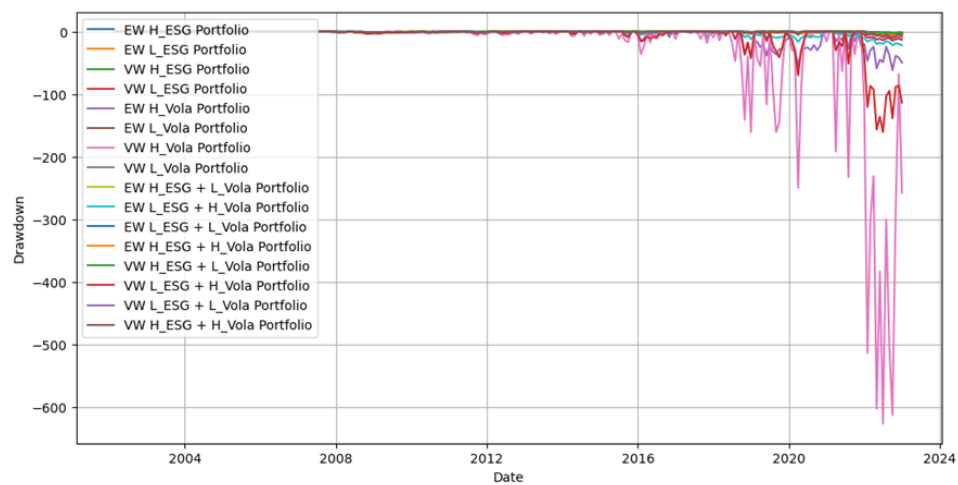


Exhibit 8: Drawdowns of all Portfolios in the In-Sample period

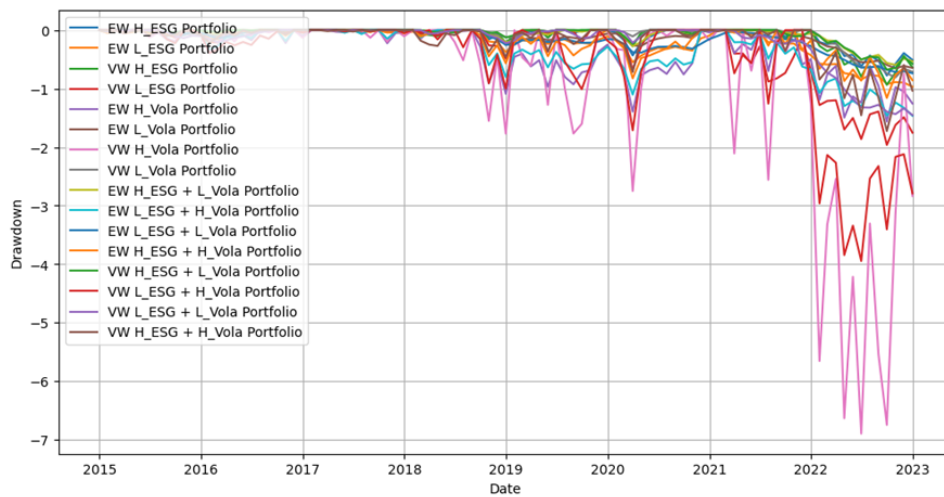


Exhibit 9: Drawdowns of all Portfolios in the Out-Sample period

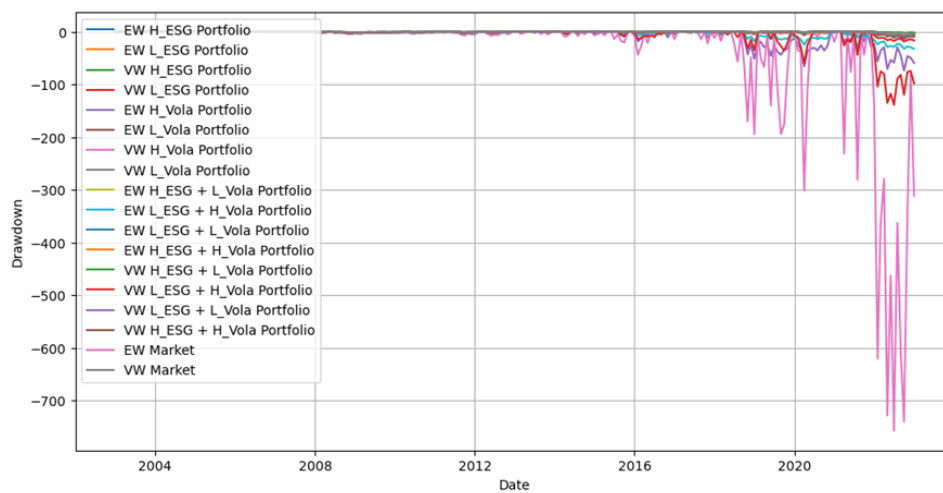


Exhibit 10: Drawdowns of all Portfolios in the Full-Sample period