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ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES - AGE-RELATED INVESTING: IS FIRM AGE A GOOD PREDICTOR OF FUTURE STOCK RETURNS?

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Abstract

This study analyses the impact of constructing a quantitative investment strategy based on information regarding firm age. The strategy is constructed based on the view that younger companies tend to outperform their peers, an idea that is verified by the performance results of the strategy. Additionally, the study goes one step further and analyses the impact of combining this information with information regarding the firms' R&D investment policies into a combined information set, then used to construct an additional strategy, whose performance reveals that this combination generates significant returns.

Keywords: Finance, Quantitative Investing, Firm Age, R&D Investing, Volatility Timing, Portfolio Management

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1. Introduction

Companies are adaptable organizations with restructuring capacity to meet changing needs, in constantly evolving markets, so there should not be any inherent reason for them to age. In reality, they should possess the learning capacity, which can occur through experience or by investing in Research and Development, that can be enhanced by investing in human capital, and getting insights from companies in their industry or others (Bahk and Gort 1993).

However, the economic literature shows that this is not the case, that companies do in fact age, and that aging is associated with lower profitability (Loderer and Waelchli 2010). These authors identify two explanations for this phenomenon: organizational rigidities because successful companies tend to codify their approach through organization and processes, and rent-seeking behavior exacerbated by aging.

This study uses this information to create a quantitative investment strategy where firm age is the strategy's main signal, used in selecting stocks and consequently constructing portfolios that are expected to generate significant returns and have relevant risk-adjusted performance. The strategy's performance verifies that, in fact, age is negatively related to profitability and that stocks of younger companies tend to outperform those of older companies. These results are obtained by analyzing the historical performance, from 2000 to 2022, of the stocks that currently constitute the Nasdaq Composite index.

In addition to this analysis, and in an effort to broaden the scope of this research, the study also seeks to understand whether combining the age signal with a signal encompassing information regarding the company's Research and Development policies, in this case, the R&D-to-market ratio, would improve the strategy's performance. This hypothesis comes from the financial literature view that R&D investing improves the company's profitability (Al-Horani 2003, Bae 2003, Chambers 2002, Duqi 2011, VanderPal 2014) and financial sustainability (Dave 2013).

Furthermore, because this strategy is based on historical data, its results are affected by various externalities. Considering the sample period, the most relevant events to impact this strategy's historical performance are the burst of the dot-com bubble (2000-2002), which is relevant in this particular case, especially for young tech companies, the global financial crisis of 2008, and the Covid-19 pandemic (2020-2021) that affected the out-of-sample performance.

2. Data

The universe of investible securities used to conduct the proposed analysis is based on the Nasdaq Composite Index (COMP), the market cap-weighted (value-weighted) index that best represents the universe of companies listed on the Nasdaq Stock Exchange, covering over 3000 stocks. Detailed Nasdaq Composite index industry breakdown in the Appendix (Exhibit 1).

The use of this index as the benchmark for this analysis is based on several reasons. The first is due to the importance of the Nasdaq exchange on the global financial landscape. The second reason, and probably the most relevant, relates to the tech-heavy nature of the index, seen in the weight the technological sector has in the index (57.21%). This strong association with the tech sector is particularly relevant for this study because the economic literature highlights that the effect that investing in Research and Development has on market value, and corporate performance, is notably more significant for companies operating in hi-tech sectors (Duqi 2013). The third reason for the choice of this index, favored over the Nasdaq-100 index or the S&P 500, is linked to its size in terms of the number of constituents. This is relevant because having a sample with more observations improves the statistical significance and robustness of results and enhances the relevance of the conclusions.

The data used in the study was retrieved from the Global Factor Data, via WRDS, a database based on the work of Jensen, Kelly, and Pederson (2022). From this database was retrieved all the necessary information to construct and analyze the strategy's historical performance including the signals (age, R&D-to-sales, and R&D-to-market), and the stocks' identifiers (permno), corresponding size group, market capitalization, prices, returns in USD, and excess returns in USD. Important to mention that all the information retrieved from Global Factor Data is on a monthly frequency, meaning the performance of the strategy was evaluated using monthly excess returns.

Moreover, according to the Global Factor Data documentation, the age signal represents the firm's age as the number of months between month *t* and the first month that its stock appears in CRSP, and is based on the firm age signal construct by Jiang, Lee, and Zhang (2005). The R&D-to-sales and R&D-to-market signals represent the company's R&D investment using two different ratios, the R&D-to-sales ratio which divides its R&D expenses at month *t* by its sales, and the R&D-to-market ratio that divides its R&D expenses at month *t* by its market capitalization in month *t*. The stock prices and returns data are from CRSP and excess returns are relative to the U.S. Treasury bill rate (Jesen, Kelly, and Pederson 2022).

To use the retrieved data for the study some preparatory measures were taken and preliminary analyses were conducted. The most important measure taken to ensure the usability of the data was to filter the data to eliminate any observations with missing data for any of the variables, which led to a filtered dataset with 205 270 observations and 1825 unique stocks. The dataset was then sorted by date to ensure the analysis was chronologically accurate. The preliminary analysis revealed that the sample is dominated by micro companies (828), followed by small (477), nano (250), large (191), and mega (79), in terms of size group. In terms of the signal distribution, it is noticeable that for all three signals, the distribution of observations is positively skewed (heavier presence of smaller signal values), meaning that the sample is dominated by younger companies and companies with more conservative R&D investment policies. Additionally, from this analysis, it was also possible to choose the R&D-to-market signal for the strategy construction as the proxy for R&D investment since outliers less impacted its distribution of values than the R&D-to-sales signal distribution. A detailed description of the signals' distribution of values is in Exhibits 2 and 3, in the Appendix.

The sample data ranges from January 2000 to December 2022 and is divided into two periods: the in-sample period (from January 2000 to December 2015) and the out-of-sample period (from January 2016 to December 2022). Overall this division is relevant to ensure the strategy's reliability and to prevent overfitting (results that are artificially inflated in the in-sample period and that do not hold in the out-of-sample).

3. Methodology

Implementing the strategy requires, firstly, the securities to be ranked monthly based on the firm age and R&D-to-market ratio signals, with the subsequent purpose of being grouped into several equal-sized portfolios according to each security's signal ranking in the sample.

Following the belief that stocks of younger firms tend to outperformance those of older firms, the age ranking system is created in such a way that, in each month, the stocks are ranked ascendingly by age meaning that the stock with the lowest corresponding age signal value (youngest companies) gets the highest ranking (rank 1) and the stock with the highest age signal value (oldest company) is awarded the lowest ranking. For the R&D-to-market signal, the opposite is true, this signal's corresponding ranking system is created in such a way that stocks of companies that invest more in Research and Development concerning their market capitalization (companies with a high R&D-to-market ratio) are ranked higher than stocks of companies with low R&D-to-market ratios, meaning that stocks are monthly ranked from high to low according to this signal.

In an effort to evaluate the aggregated effect of these signals, there was a need to create an additional ranking system that coupled these core ranking systems into one combined metric. However, because there does not seem to exist, in the financial literature, a general and explicit understanding of the relationship between age and R&D investment and their combined effect on performance, instead of creating only one combined ranking there was the necessity to create two ranking systems: the combined ranking system, and the alternative combined ranking system. The combined ranking system is based on the hypothesis that younger companies that invest more than their peers in R&D will outperform them, and so this ranking is just a weighted average of the original age (65%) and R&D-to-market rankings (35%). The alternative ranking system is set to evaluate the hypothesis that younger firms with low levels of R&D investment will outperform their peers, and so the ranking system is a weighted average (same as above) of the age ranking system and the inversed R&D-to-market ranking (companies ascendingly ranked from low to high values of R&D-to-market, ence R&D investment). Moreover, by creating these opposed ranking systems and evaluating the performance of portfolios formed through them, arises the expectation of understanding which of these hypotheses holds true.

After applying the ranking systems (R&D-to-market ranking will not be used to construct a separate independent strategy, it will only be used to construct the combined strategies since evaluating the R&D-to-market signal alone is not the purpose of this study) to each month of the in-sample period, different portfolios could be formed using the results from the rankings. For each ranking system, it was possible to group the stocks into decile portfolios, on a monthly basis, where the 10% best-ranked stocks formed the top portfolio (portfolio with label 1 and with the best expected performance), the 10%-20% best-ranked stocks formed the second portfolio, and so on until the stocks with the 10% worst ranking formed the bottom portfolio (with label 10), the portfolio with the worst expected performance.

In order to analyze the performance of the signals and to evaluate their ability, or not, to satisfactorily predict future returns, the decile portfolios were used to construct a Long Top-decile portfolio and a Long Bottom-decile portfolio. Additionally, a net zero-investment Long-Short portfolio is also created based on the previously mentioned assumption that the top-decile portfolio is expected to perform the best and the bottom-decile portfolio is expected to perform the worst, therefore forming this portfolio by holding long the Top-decile portfolio and holding short the Bottom-decile portfolio. Additionally, these portfolios are constructed as value-weighted portfolios, where each stock's weight on the portfolio is based on its corresponding company's market capitalization. All portfolios are monthly rebalanced, in line with the monthly ranking of stocks, and their returns are excess returns. All portfolios were created in the in-sample period, and subsequently applied to the out-of-sample period for testing.

The naive performance analysis approach is used to evaluate the strategies' performance using metrics: annualized average monthly returns, annualized standard deviations, and Sharpe ratios. The performance of these strategies is compared with the performance of the value-weighted portfolio comprised of all investible securities in the sample, which is used as a proxy of the Nasdaq Composite index (this portfolio is not expected to perform so closely to the index itself due to the filtering that was done to the dataset to eliminate observation with missing data).

Moreover, this analysis omits some well-recognized risk factors that try to explain abnormal excess returns. To evaluate the performance of the strategy concerning these risk factors, time-series regressions on the Fama-French Five-Factor Model were run. The Fama-French 5-factor model is a result of the work of Fama and French (2015), which extended their previous work (Fama and French 1992) where the size (SML) and value (HML) factors were introduced to the traditional market risk premium (Mkt-Rf) from the Capital Asset Pricing Model (CAPM) of Sharpe (1964). In the most recent work, they introduced two additional risk factors: profitability (RMW) and investment (CMA). The historical data for these factors was retrieved via WRDS.

In an attempt to improve the age signal strategy, the core strategy of this study, a volatility timing technique was employed for the Age Value-weighted Long Top-decile portfolio. The employment of this technique is rooted in the underlying idea that stock returns of younger lessconsolidated companies are more volatile than those of older more established firms. This technique was implemented by constructing a managed volatility portfolio from this age portfolio on the idea of two-fund separation, where in times of low volatility more weight is given to the risky asset (age portfolio), and in high volatility months more weight is given to risk-free asset, and less is given to the age portfolio. A detailed description of the portfolio's construction is in Exhibit 4, in the Appendix.

Ultimately, to assess the practical applicability and robustness of the strategy to changes in the economic environment, the out-of-sample performance of the strategy was conducted using portfolios constructed with observations from 2016/01 to 2022/12.

4. Results

The first important set of results to analyze is the in-sample naive performance of the value-weighted Long Top-decile, Long Bottom-decile, and Long-Short portfolios, for the three signals. As mentioned, the performance analysis of these portfolios is compared with the in-sample performance of the value-weighted Long-only portfolio of all available stocks in the sample. Table 1 displays these results.

Table 1 – In-sample naive performance of signals' Long Top-decile, Long Bottom-decile, and Long-Short portfolios, and the Nasdaq proxy portfolio

		Annual Return (%)	*Annual Std Dev (%)*	*Sharpe Ratio*
Age	Top	36.356	36.178	1.005
	Bottom	11.288	25.822	0.437
	Long-Short	25.068	29.566	0.848
Combined	Top	15.343	42.652	0.360
	Bottom	19.476	24.999	0.779
	Long-Short	- 4.133	32.822	- 0.126
Alternative	Top	33.708	32.591	1.034
	Bottom	6.520	27.203	0.210
	Long-Short	27.188	28.360	0.959
Nasdaq proxy	Long-only	15.340	23.208	0.661

Considering the age signal's portfolios, the first conclusion to take from these results is the evident overperformance of the Long Top-decile portfolio related to the Long Bottom-decile portfolio, both in absolute performance (generates higher annualized monthly returns) and risk-adjusted performance (presents a higher Sharpe Ratio), a result that is also validated by the positive performance of the signals' Long-Short portfolio (if the opposite was true and the Bottom-decile portfolio out-performed the Top-decile portfolio the Long-Short should generate negative returns and Sharpe Ratio). Nonetheless, the Long-Short portfolio's returns and Sharpe Ratio are lower than those of the Top-decile portfolio because its performance is negatively impacted by the positive, although moderate, performance of the Bottom-decile portfolio. Additionally, it is also important to mention that the Long Top-decile portfolio, despite generating the highest returns and having the best risk-adjusted performance, is also the age signal portfolio with the highest annual standard deviation (or volatility), implicating it is the portfolio most exposed to risk. More importantly, these results corroborate the previously documented economic view that younger companies tend to outperform older companies.

Considering the combined ranking system's portfolio, the main takeaway is the apparent overperformance of the bottom-decile portfolio relative to the top-decile portfolio, with higher returns and lower volatility resulting in a higher Sharpe Ratio (0.779 against 0.360 of the top-decile portfolio). Due to this, the Long-Short portfolio generates negative returns and subsequent negative Sharpe Ratio. These results imply that the hypothesis this signal is set to study does not hold, meaning that young innovative companies do not outperform their peers, opposetely, these results show that older less innovative companies (companies that form the combined Bottom-decile portfolio) are the better performers.

For the alternative ranking system, the results imply that the best-performing portfolio is the Long Top-decile portfolio, the portfolio that generates the higher returns (33.708%) and the best risk-adjusted performance (Sharpe Ratio of 1.034). The Long Bottom-decile performs very moderately, with an annualized monthly return of 6.520% and a Sharpe Ratio of 0.210. As a consequence, the alternative combined Long-Short portfolio presents promising results (Sharpe Ratio of 0.959), although not as promising as the Top-decile portfolio. These results lead to the conclusion that the hypothesis this signal is set to verify holds true and that younger less innovative companies tend to outperform their peers (in this case older and innovative companies that form the alternative combined Long Bottom-decile portfolio).

Additionally, and considering the in-sample performance of the Long-only portfolio used as a proxy of the Nasdaq Composite index (benchmark of the strategy): annualized monthly return of 15.340%, annual volatility of 23.208%, and Sharpe Ratio of 0.661; it is relevant to point out that the signals best-performing portfolios (age Top-decile and Long-Short portfolios, combined Bottom-decile portfolio, and alternative combined Top-decile and Long-Short portfolios) all perform better than the Nasdaq, in the in-sample period.

These results are supported by the portfolios' evolution of cumulative returns, shown in Exhibit 5 in the Appendix, which shows that the age Long Top-decile portfolio generates the highest cumulative returns, peaking at over 120 (12,000%) in 2015, followed by the alternative combined Long Top-decile portfolio (peaked at almost 100 in 2015). This was expected since these are the portfolios with the highest returns and Sharpe Ratio (both above 1, meaning the returns generated exceed the risk taken). The graphical representation of portfolios' drawdown (representation of the downside risk of the portfolios' returns), shown in Exhibit x.6 in the Appendix, also supports the results of the naive performance of the portfolios, because it shows that the age Long Top-decile portfolio and the alternative Long Top-decile portfolio are the most exposed to downside risk, a conclusion that is expected since these portfolios have some of the highest levels of volatility is the sample (36.178% and 32.591%, respectively).

Table 2 – In-sample performance of the signal's Long Top-decile, Long Bottom-decile, and Long-Short portfolios on the Fama-French 5-factor model risk factors

		$Alpha$ *(t-value)*	β_{MktRf} (t-value)	β_{SMB} (t-value)	β_{HML} (t-value)	β_{RMW} (t-value)	β_{CMA} (t-value)	IR	R^2
Age	Top	0.033 (6.955)	1.650 (8.681)	0.590 (3.501)	-0.607 (-3.027)	-0.667 (-3.117)	-0.817 (-2.861)	0.536	0.663
	Bottom	0.007 (2.109)	1.217 (14.05)	-0.019 (-0.158)	-0.458 (-3.235)	-0.293 (-1.943)	0.379 (1.880)	0.163	0.670
	Long-Short	0.026 (4.380)	-0.151 (-0.989)	0.609 (2.895)	-0.149 (-0.596)	-0.374 (-1.399)	-1.20 (-3.356)	0.338	0.214
Combined	Top	0.015 (3.553)	1.197 (11.300)	0.891 (6.128)	-0.295 (-1.700)	-1.611 (-8.723)	-0.121 (-0.490)	0.274	0.819
	Bottom	0.014 (4.108)	1.171 (13.152)	0.038 (0.313)	-0.500 (-3.434)	-0.054 (-0.348)	0.045 (0.218)	0.317	0.628
	Long-Short	0.000 (0.079)	0.026 (0.192)	0.853 (4.635)	0.205 (0.938)	-1.557 (-6.663)	-0.166 (-0.532)	0.006	0.512
Alternative	Top	0.030 (7.435)	1.075 (10.328)	0.496 (3.474)	-0.564 (-3.315)	-0.555 (-3.060)	-0.678 (-2.801)	0.573	0.701
	Bottom	0.001 (0.405)	1.377 (15.091)	-0.192 (-1.532)	-0.311 (-2.084)	-0.307 (-1.928)	0.735 (3.463)	0.031	0.670
	Long-Short	0.028 (5.221)	-0.302 (-2.140)	0.688 (3.552)	-0.253 (-1.097)	-0.248 (-1.010)	-1.414 (-4.305)	0.402	0.274

Analyzing the results displayed in Table 2 yields additional findings to support the previous analysis regarding the signals' portfolios performance. The first finding that corroborates the results from the naive performance of the portfolios is that the best-performing portfolios (in terms of generated returns and Sharpe Ratio) also produce the highest alphas. The age Top-decile portfolio produces an alpha of 0.033, the alternative Top-decile portfolio an alpha of 0.030, the age Long-Short an alpha of 0.026, and the alternative Long-Short portfolio an alpha of 0.028, all statistically significant. These results show evidence that these portfolios yield significant returns in excess of the risk factors.

Additionally, from the analysis of the betas on the risk factors, it is possible to identify common traits in all portfolios. All portfolios, excluding the age Long-Short and alternative Long-Short portfolios, appear to move in line with the market, meaning their returns are positively correlated with the market returns because they have positive betas on the market factor. Moreover, their betas are positive and above 1, meaning their returns are more volatile than the market. Regarding the betas on the other factors, and always with a few exceptions, these suggest that all portfolios are: positively exposed to the size (SMB) factor (excluding the age and alternative bottom-decile portfolios) which is reasonable since these portfolios' returns are mostly affected by the return of younger, consequently smaller, firms (the sample is also dominated by small cap stocks); negatively exposed to the value (HML) factor, which is also reasonable since the majority of these portfolios are composed of younger companies, with a more growth than value nature; and negatively exposed to the profitability (RMW) factor, meaning their returns are more exposed to the returns of companies with weak operating profitability. However, the betas on the investment (CMA) factor do not have the same signal for all portfolios, for the Long Top-decile and Long-Short portfolios the betas are negative meaning their returns are more exposed to the returns of companies with aggressive investment strategies, and for the Long Bottom-decile, the betas are positive meaning their returns are more related to the return of moderate companies in terms of investment policies.

Finally, the Information Ratio also supports evidence that the age Long Top-decile portfolio and the alternative Long Top-decile portfolio produce the highest risk-adjusted returns in relation to the benchmark (the Fama-French 5 risk factors. The first presents an Information Ratio of 0.536, and the second an Information Ratio of 0.573.

As previously mentioned, a new portfolio based on the age Long Top-decile portfolio was created by applying a volatility timing technique to this portfolio, in an attempt to improve the high volatility of this portfolio's returns. The goal was to arrive at a strategy still with high returns but with reduced volatility, and a better risk-adjusted performance. The in-sample performance of this strategy was as follows: annualized monthly returns of 37.325%, an annual standard deviation of 35.587% (36.178% for the age Top-decile), a Sharpe Ratio of 1.048, an alpha of 0.030, and an Information Ratio of 0.445. These results show that this managed volatility portfolio achieved higher returns, lower volatility, and a better risk-adjusted performance than the original portfolio, but with a worse performance when related to the risk factors. However, it is considered that the main goal of this strategy improvement was not fully accomplished because the returns of this portfolio are only slightly less volatile than those of the age portfolio, meaning the desired significant volatility reduction was not achieved. The evolution of cumulative returns and the graphical representation of the drawdown for this portfolio are shown in Exhibit 7, in Appendix.

Table 3 – Out-of-sample naive performance of signals' Long Top-decile, Long Bottom-decile, and Long-Short portfolios, the managed volatility portfolio, and the Nasdaq

		Annual Return (%)	*Annual Std Dev (%)*	*Sharpe Ratio*
Age	Top	66.720	73.229	0.911
	Bottom	24.517	21.487	1.141
	Long-Short	42.203	69.477	0.607
Combined	Top	01.873	35.612	0.053
	Bottom	24.262	20.710	1.172
	Long-Short	- 22.389	29.779	-0.752
Alternative	Top	54.151	50.119	1.080
	Bottom	13.648	21.165	0.645
	Long-Short	40.502	45.906	0.882
Age Managed Volatility		67.990	56.456	1.204
Nasday proxy	Long-only	24.102	20.425	1.180

The results of the out-of-sample historic performance of the portfolio, displayed in Table 3, show that the age Long Top-decile portfolio continues to have the best performance, in absolute terms (annual return of 66.720%), out of the signals' portfolios, but not the best risk-adjusted performance, due to a significant increase in volatility (annual standard deviation of 73.229%) that led the Sharpe Ratio to fall below 1 (returns generated do not compensate the risk taken). All other portfolios appear to maintain their performance. The only exception is the age Long Bottom-decile portfolio, which increased its returns by 13 percentage points (11% to 24%) while decreasing its annual standard deviation by 4 percentage points (from 25% to 21%). In the out-of-sample, the in-sample best-performing portfolios (age Top-decile and alternative top-decile portfolios) continue to generate higher returns than the market (Nasdaq), however with lower risk-adjusted performance. Additionally, if in the in-sample period, the performance of the managed volatility portfolio did not fulfill its purpose, its out-of-sample performance shows differently. In this period, this portfolio generated higher returns than its benchmark (the age Long Top-decile portfolio) and was subject to significantly less volatility, resulting in a substantially better risk-adjusted performance (Sharpe Ratio of 1.204 against 0.911 of the age Top-decile portfolio). The evolution of cumulative returns and the drawdown can be seen in Exhibit 8 in the Appendix. The full-sample historical performance is in Exhibit 9, in the Appendix.

5. Limitations

As with any investment strategy, there are some factors, such as transaction costs, liquidity issues, or short-selling constraints, that can affect the strategy's implementation and prevent it from achieving its desired performance. In the particular case of this strategy, the biggest implementation issue is the high level of trading required to construct and manage the portfolio. This is mainly due to the high number of stocks that constitute the portfolio and the monthly rebalancing required to ensure the strategy's accuracy, which leads to heavy trading costs. This strategy is also affected by survivorship bias because using the current constituents of the Nasdaq Composite index to construct the strategy undermines the effect of loser stocks (companies with bad performance with risk of filing for bankruptcy) that left the index and were replaced by winner stocks, a fact that may have overestimated its performance. These implementation issues are more significant for retail investors who may not be able to employ active investment practices, mainly active portfolio management, leading to suboptimal portfolio construction and asset allocation. Other issues, more related to data constraints are noteworthy. Mainly the fact that there was no available signal information on some stocks on the Nasdaq Composite index during the entire sample period, meaning the portfolio used as the proxy for this index does not perfectly replicate the index's historical performance.

6. Conclusion

Overall, the results indicate that believing that the company's age is a good predictor of stock returns and that using that information as the main signal to construct a quantitative investment strategy is a very reasonable assumption that yields significant returns and overperforms the benchmark, in this case the Nasdaq. This supports the view that stocks of younger companies tend to outperform those of older companies, corroborating previous findings on this issue.

Additionally, these results also shed light on the mostly unrealized relationship between the company's age and R&D investment policy, and their combined effect on performance. The results show that the best-performing portfolio, constructed as a combination of the age and R&D-to-market signals, is distinguished by investing in younger companies with lower R&D-to-market ratios, holding true the hypothesis that younger companies with moderate R&D investment policies tend to outperform their peers. This conclusion may seem unreasonable considering the economic view that R&D investing is positively related to performance, however, a plausible explanation for these findings is that the positive effect of R&D on a company's performance is not immediate, in fact, it negatively impacts the short-term performance, so it is plausible to expect that young companies with more moderate R&D investment policies outperforms young companies with aggressive R&D policies.

In conclusion, the evidence proves that the age strategy is a good investment strategy, that investors should consider adopting, especially investors with lower risk aversion. For investors with higher levels of risk aversion, this alternative combined strategy is a better strategy, that does not yield the same level of returns but achieves better risk-adjusted returns because of lower volatility of returns. The managed volatility strategy generates higher returns than this alternative combined strategy and has a better risk-adjusted performance than the age strategy, but is the most challenging to implement.

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Appendix

Exhibit 1 - Industry breakdown of the Nasdaq Composite index, as of November 2023.

Industry	Weight
Basic Materials	1.29%
Consumer Discretionary	17.94%
Consumer Staples	2.76%
Energy	0.89%
Financials	3.47%
Health Care	7.02%
Industrials	4.36%
Real Estate	0.96%
Technology	57.21%
Telecommunications	3.19%
Utilities	0.91%

Exhibit 2 - Description of the age signal distribution of values

Because age is a signal that evolves linearly (in each month the age always increases 1 unit from the previous month), the best way to analyze the signal's distribution of values is to consider only the observations for the last month of the sample. From this we can then understand who is the youngest, and oldest companies, and the average age of companies in the sample:

	Age (months)	*Security Permno*
Youngest Company	24	19558
Oldest Company	1163	13856
Average Age	219	

From this, we can already understand that the signal's distribution of values is positively skewed, because the average value is closer to the minimum than the maximum, which means that the signal is dominated by younger companies. The histogram of the age distribution of values evidences this idea:

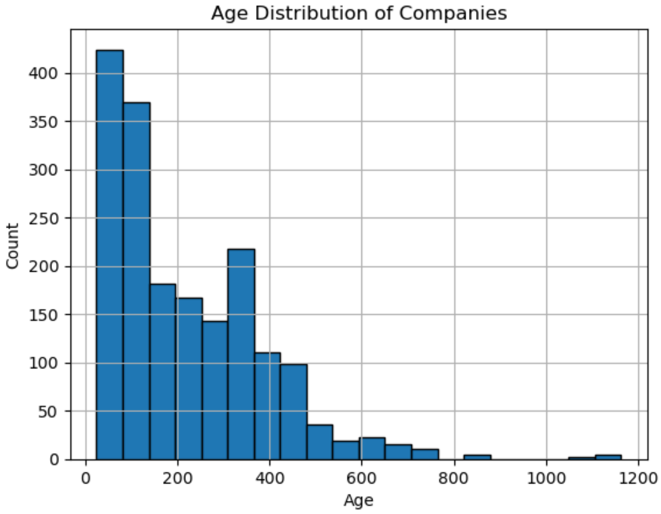
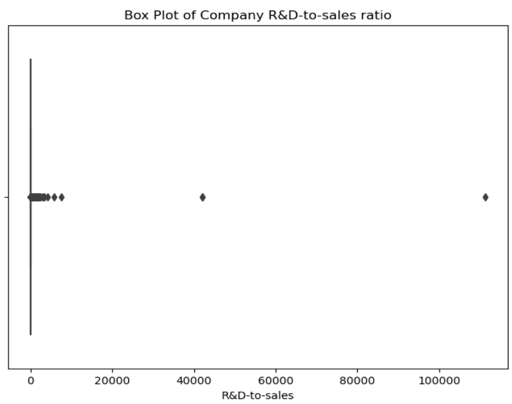
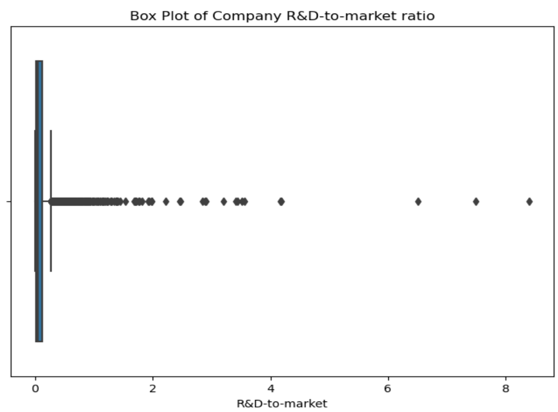


Exhibit 3 - Description of the R&D-to-market and R&D-to-sales signals distribution of values

We had two signals to represent the effect of companies' R&D investment policies on performance, the R&D-to-market ratio and the R&D-to-sales ratio. Both signals evaluate the relative importance given to R&D practices and innovation, the first measures this importance relative to the company's size (market capitalization), and the second measures this against the company's sales or revenues. At first glance, it is not clear which signal best captures this effect, so, in order to choose the signal to implement in the strategy we analyzed the signals' distribution of values, and chose the signal with a less dispersed distribution with a reduced incidence of outliers. The signals' box plots show the distribution of values and the presence of outliers.





These box plots show that both signals have a significant presence of outliers, but we can clearly see, even by analyzing the scale of the signals' values that for the R&D-to-market their presence is less significant than for the R&D-to-sales, which leads to the decision of choosing the R&D-to-market signal as the one to use to construct the strategy.

Exhibit 4 – Detailed Description of the construction of the Managed Volatility Portfolio

As seen in the results, the age Long Top-decile portfolio is the best-performing portfolio constructed using the core signal of the strategy (age signal), which consequently makes this the most relevant strategy portfolio. However, this portfolio is not the strategy's best-performing portfolio in relation to the risk-adjusted performance (Sharpe Ratio), because its returns are highly volatile (annual standard deviation of 36.178% in the in-sample period and 73.229% in the out-of-sample period). So, in an attempt to improve the performance of this portfolio, with the main purpose of reducing the volatility while still generating high returns, we employed a volatility timing technique to create a managed volatility portfolio, a modified version of the age Long Top-decile portfolio.

This modification is focused on the idea of two-fund separation, which means allocating between the risky asset (in this case the age Top-decile portfolio whose returns are already calculated and taken as given) and the risk-free asset. This is based on the work of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Moreira and Muir (2017). So the idea is to put more weight on the age portfolio in periods of low volatility, and inversely in periods of high volatility put more weight on the risk-free asset, and this is achieved by creating 3-month rolling windows so that the weight put on the age Top-decile portfolio in month t (w_t) is calculated as the ratio of the standard deviation of the entire in-sample period (σ) to the standard deviation of the returns of three previous months ($\sigma_{t-3,t-1}$). Additionally, we added a leverage constraint of 30% to this weighting scheme in order to make the model more reasonable. Due to leverage the returns of this portfolio are calculated as follows:

$$r_{levered} = (w_t + leverage) * r_{unlevered} - leverage * r_f \quad (1)$$

But because the age portfolio returns are excess returns, the managed volatility portfolio returns can then be calculated as follows

$$r_{levered} = (w_t + leverage) * (r_{unlevered} - r_f) \quad (2)$$

Then, with our leverage constraint of 30%, we limit the weight to put on the age portfolio to a maximum of 130%. So, in conclusion, the weighting scheme used to construct the managed volatility portfolio is as follows

$$w_t = \min\left(\frac{\sigma}{\sigma_{t-4,t-1}}, 130\% \right) \quad (3)$$

Moreover, the above weighting scheme was used to construct the in-sample managed volatility portfolio, however, to analyze the out-of-sample performance of this portfolio we need to change the way the weighting scheme is defined, since it is unreasonable to consider using the standard deviation of the entire period since is any given time it possible to calculate the standard deviation of realized returns, not of future unpredictable returns, so the out-of-sample weight of month *t* is calculated as the ratio of the standard deviation of returns from the beginning of the out-of-sample period until month *t-1* ($\sigma_{1,t-1}$) to the standard deviation of the returns of the past three months ($\sigma_{t-3,t-1}$), also applying the leverage constrait

$$w_t = \min\left(\frac{\sigma_{0,t-1}}{\sigma_{t-4,t-1}}, 130\% \right) \quad (4)$$

Exhibit 5 – Graphical representation of the portfolios' in-sample evolution of cumulative returns

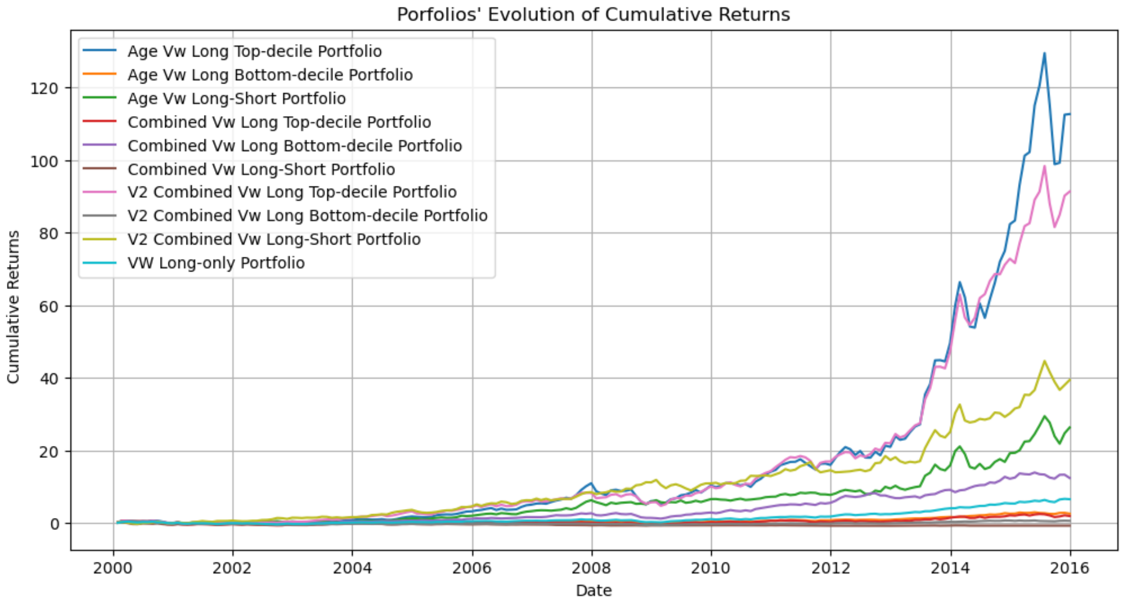


Exhibit 6 - Graphical representation of the portfolios' in-sample drawdown

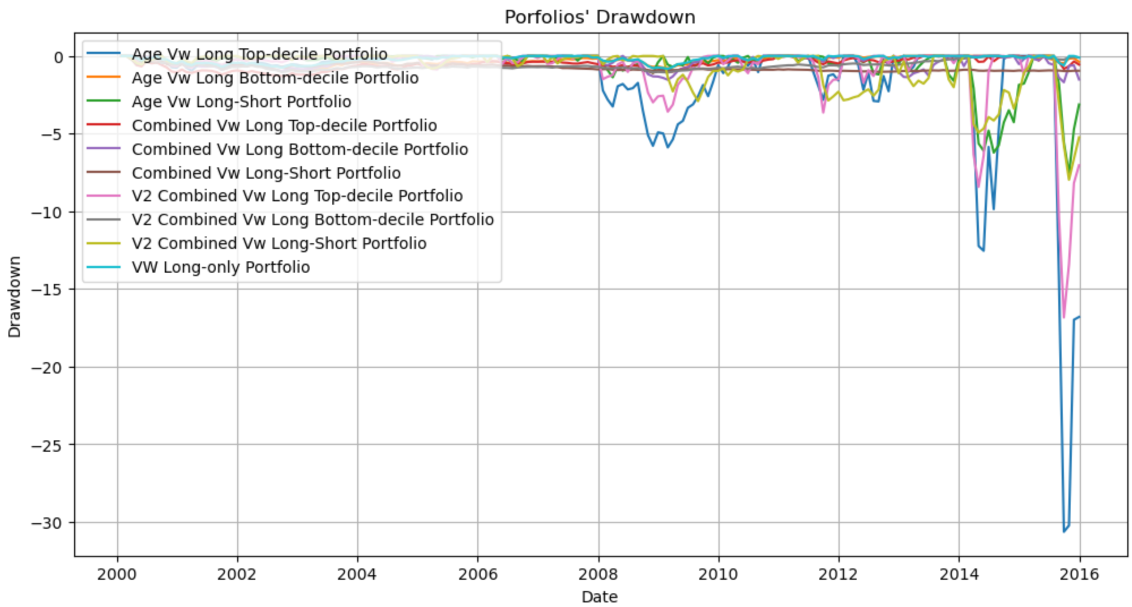


Exhibit 7 – Graphical representations of the managed volatility portfolio's in-sample evolution of cumulative returns and drawdown, and its comparison to the age Long Top-decile portfolio

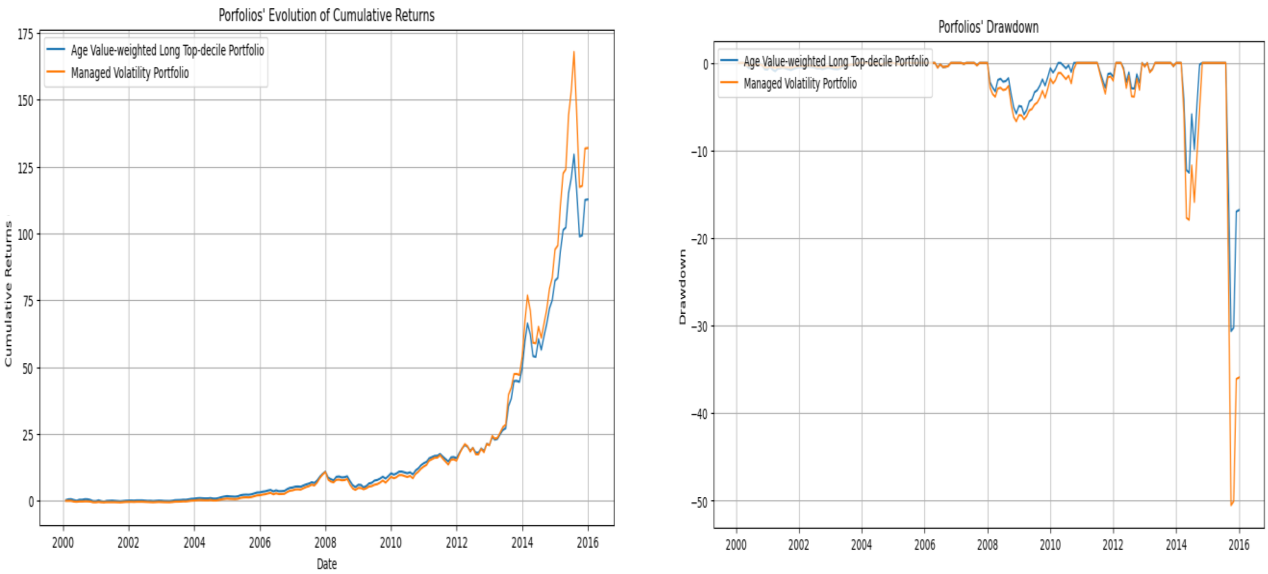
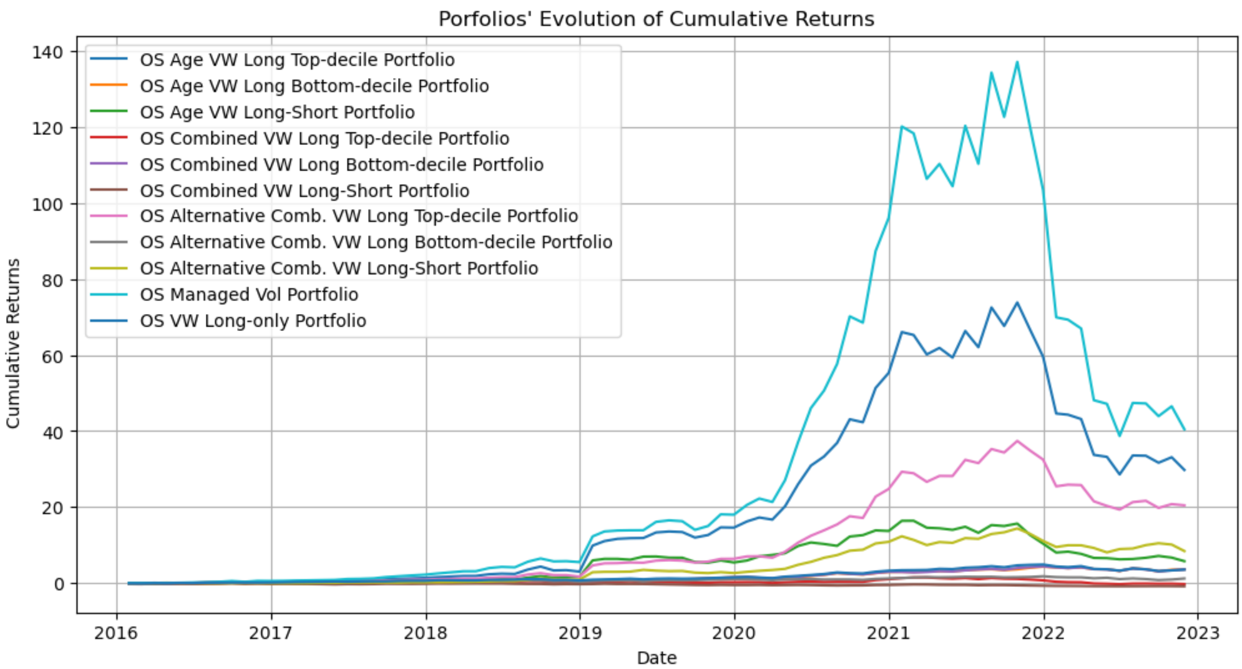


Exhibit 8 - Graphical representations of the portfolios' out-of-sample evolution of cumulative returns and drawdown



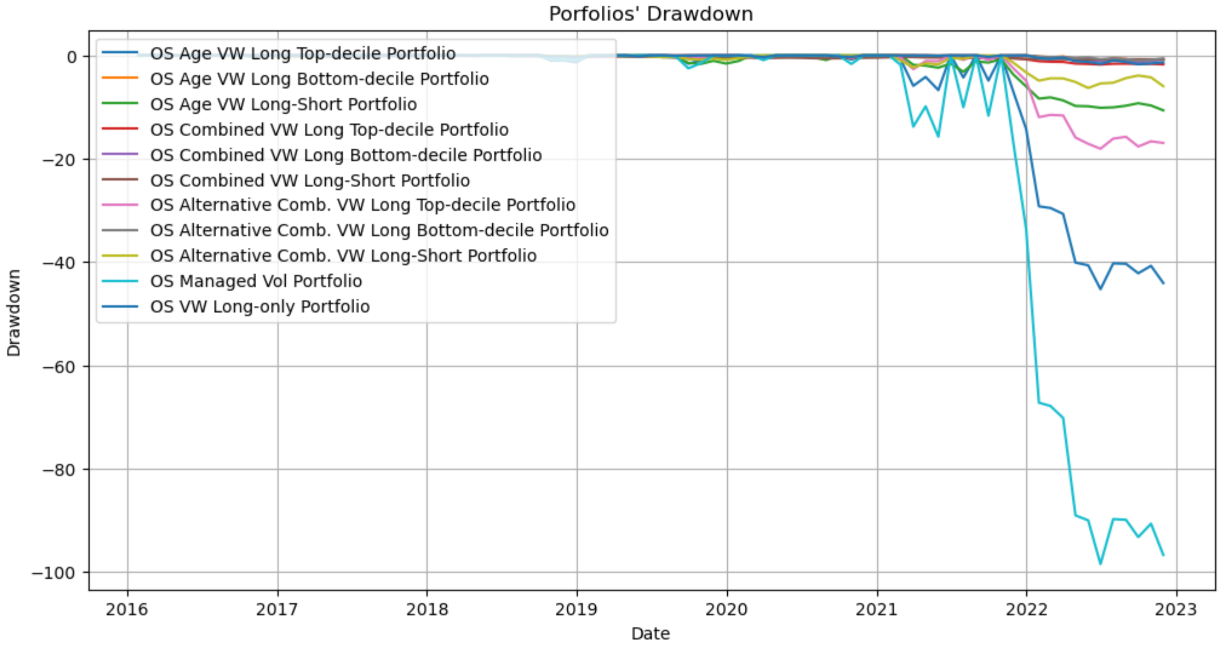


Exhibit 9 – Portfolios' full-sample naive performance results

		Annual Return (%)	*Annual Std Dev (%)*	*Sharpe Ratio*
Age	Top	45.521	50.336	0.904
	Bottom	15.281	24.618	0.621
	Long-Short	30.240	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	1.030
	Bottom	8.671	25.511	0.340
	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

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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December, 2023

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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 ΔTax & 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 beneficiated 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.

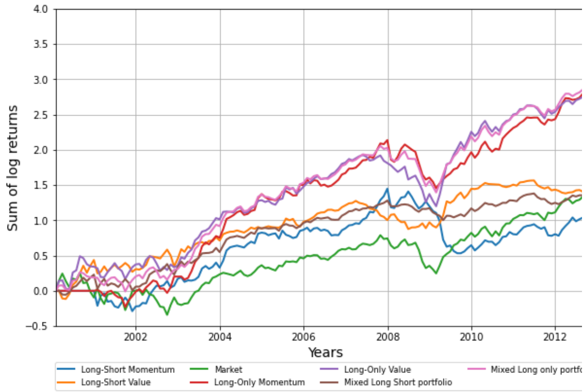

Figure 2: Cumulative Returns of the portfolios In-Sample

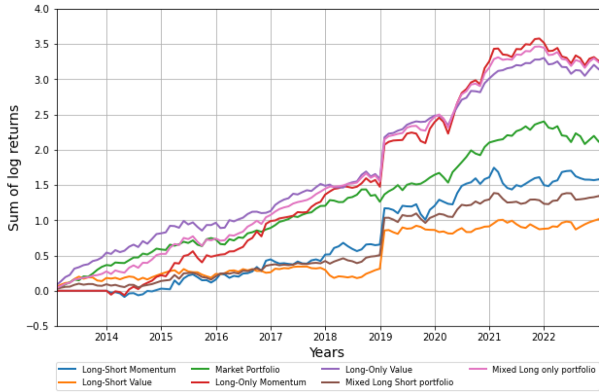

Figure 3: Cumulative Returns of the portfolios Out-of-Sample

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	0.0146	0.0110	0.0097	0.0098	0.0121
	(1.6958)	(1.9076)	(2.5220)**	(1.4289)	(2.9193)*	(1.8053)
Mkt-RF	-0.2737	0.1396	-0.0118	0.0707	-0.1428	0.10519
	(-2.5992)*	(0.8289)	(-0.1280)	(0.4716)	(-2.0263)**	(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	0.0152	0.0071	0.0129	0.0057	0.0140
	(0.975)	(1.989)**	(1.663)	(1.855)	(1.946)	(2.057)**
Mkt-RF	0.2078	0.1482	-0.0843	-0.0609	0.0617	0.0436
	(1.822)	(0.776)	(-0.761)	(-0.352)	(0.813)	(0.256)
SMB	-0.0658	0.6616	0.4985	0.3323	0.2163	0.4969
	(-0.436)	(1.914)	(3.398)*	(1.059)	(2.153)**	(1.611)
HML	-0.0831	-0.5861	0.7442	-0.2377	0.3306	-0.4119
	(-0.461)	(-1.879)	(4.250)*	(-0.840)	(2.755)*	(-1.479)
RMW	0.2927	-0.5285	-0.1049	-0.3177	0.0939	-0.4231
	(1.563)	(-1.255)	(-0.577)	(-0.831)	(0.754)	(-1.125)
CMA	0.3048	0.7846	-0.2931	0.4174	0.0058	0.6010
	(1.220)	(1.713)	(-1.207)	(1.004)	(0.035)	(1.470)
MOM	0.6514	0.0447	0.1324	-0.4153	0.3919	-0.1853
	(8.591)*	(0.180)	(1.797)	(-1.846)	(7.767)*	(-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.

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.

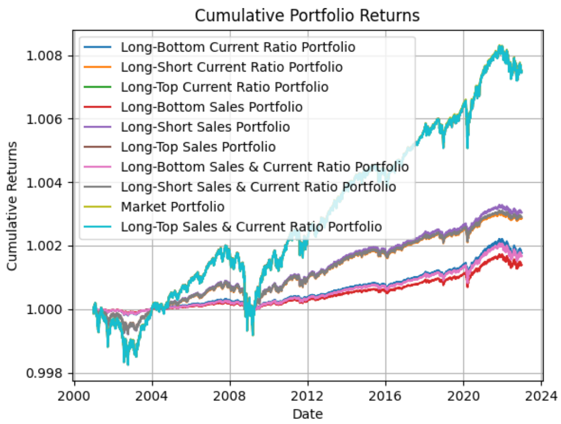

Figure 42: Portfolios' Cumulative Returns

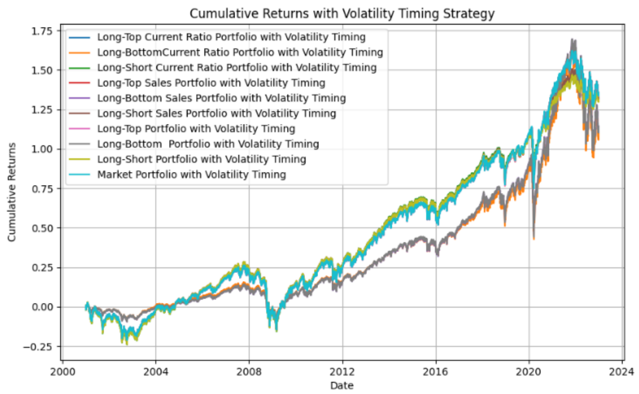

Figure 53: Portfolios' Cumulative Returns with a Volatility Timing Strategy

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 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.

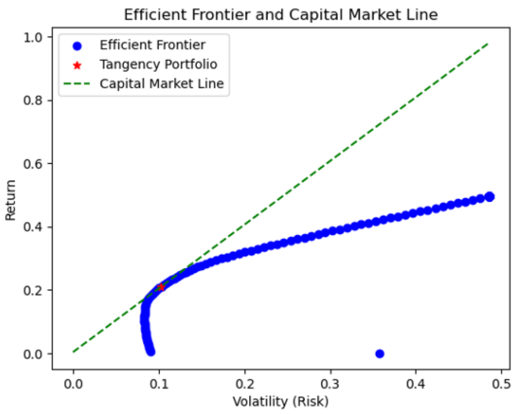

Figure 64: Efficient Frontier and Capital Market line

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.

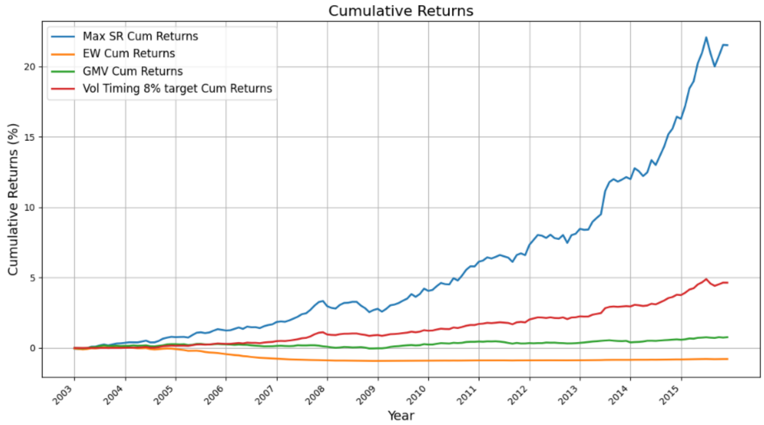

Figure 75: In-Sample Portfolios' Cumulative Returns

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.

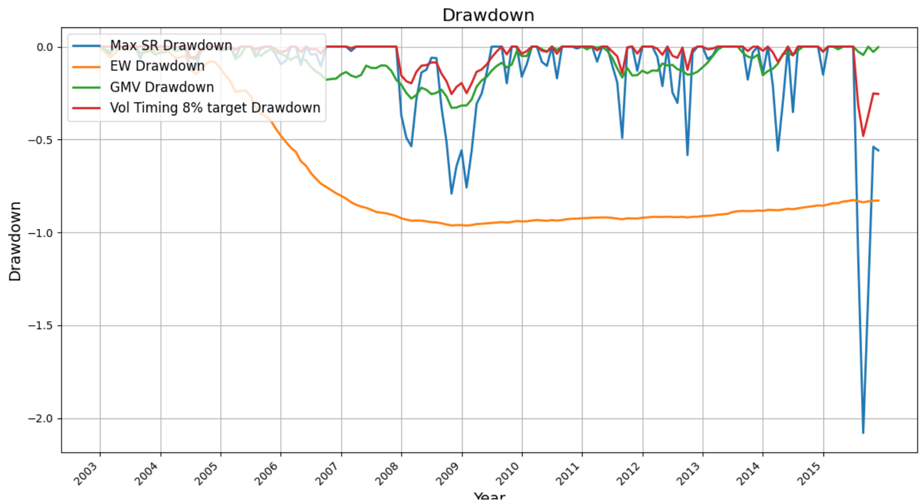

Figure 86: In-Sample Portfolios' Drawdowns

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
R^2	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 0.0091to 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 .0.56) 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.

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Appendix

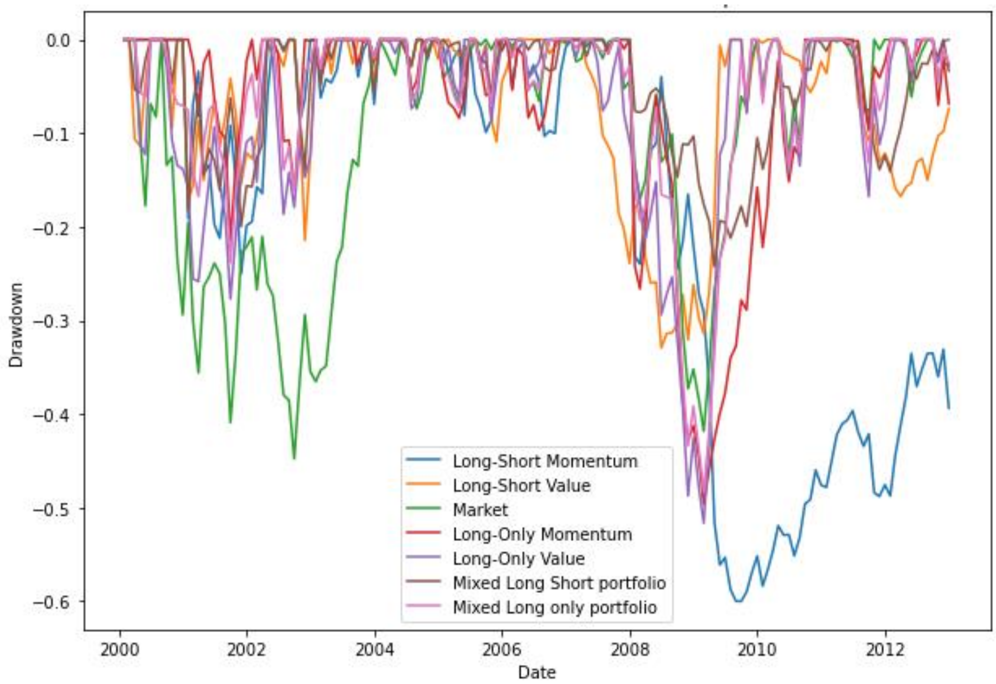

Exhibit 1: Maximum Drawdown of the Portfolios In-Sample

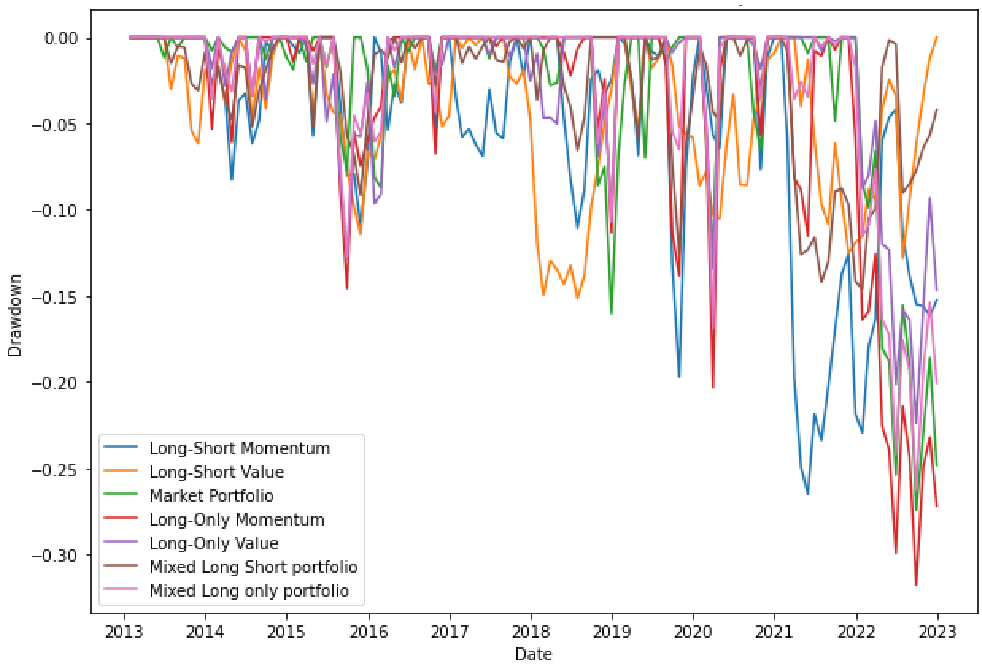

Exhibit 2: Maximum Drawdown of Portfolios Out-of-Sample

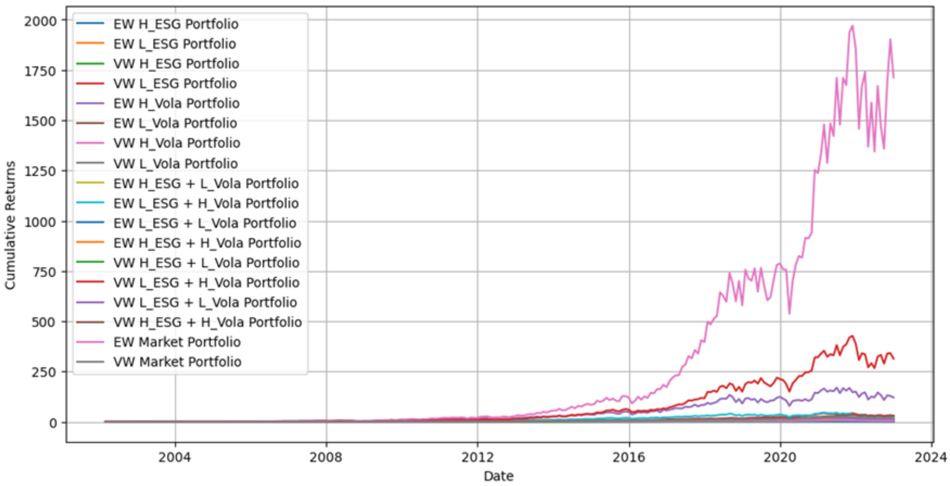

Exhibit 3: Cumulative Returns of all Portfolios in the In-Sample period

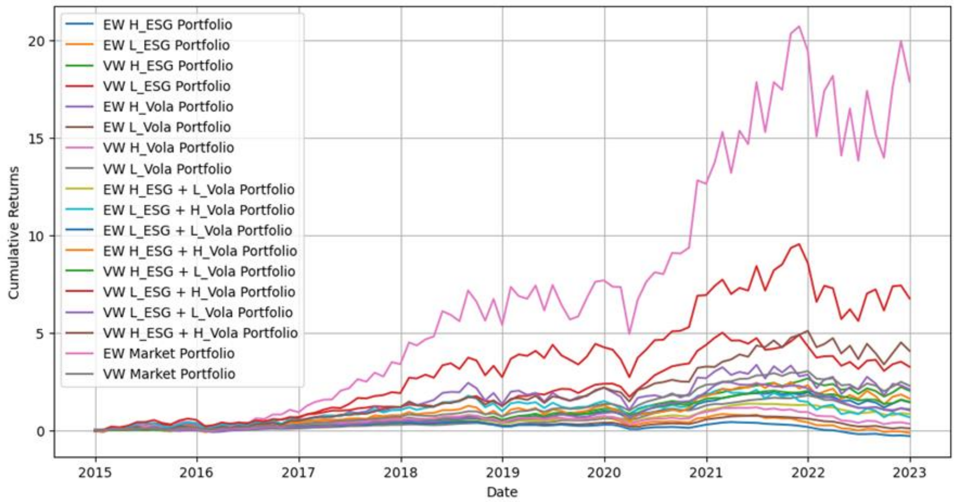

Exhibit 4: Cumulative Returns of all portfolios out-of-sample

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: Perfomance Statistics of all Portfolios

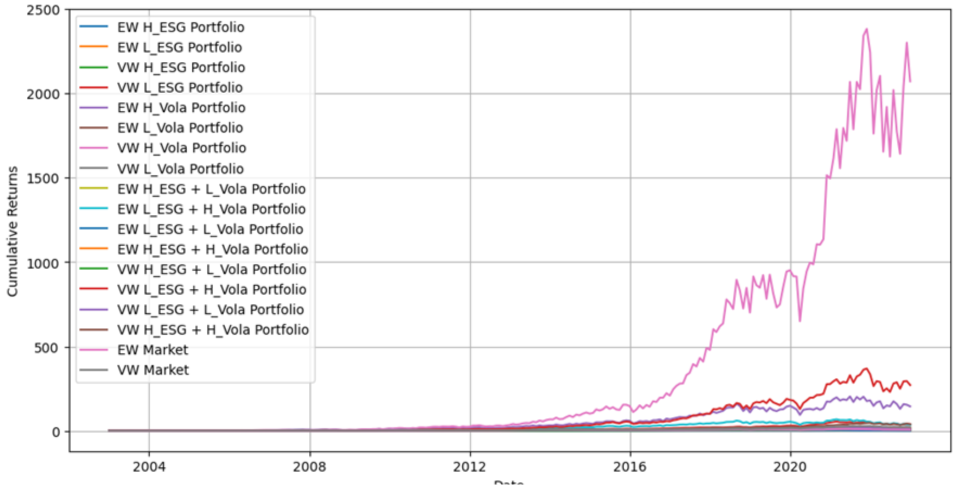

Exhibit 6: Cumulative Returns of all Portfolios in the Full-Sample period

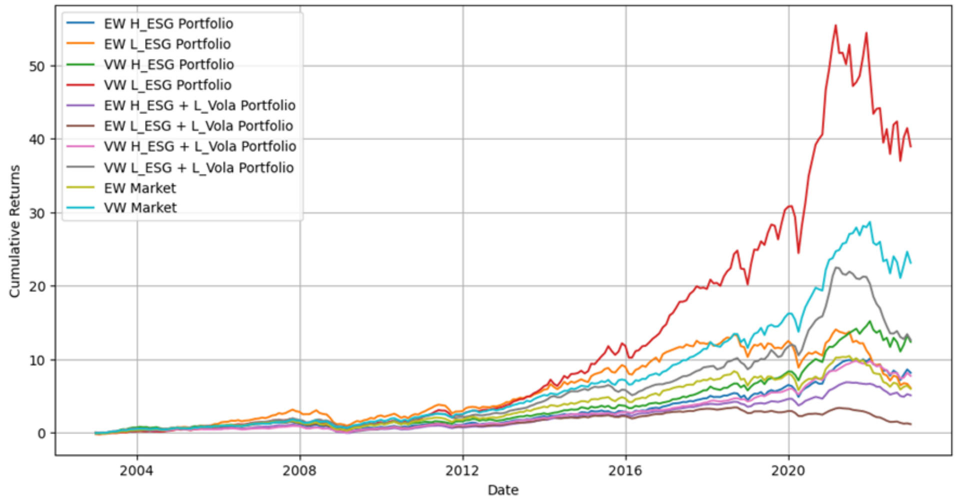

Exhibit 7: Cumulative Returns of the most relevant portfolios in the Full-Sample period

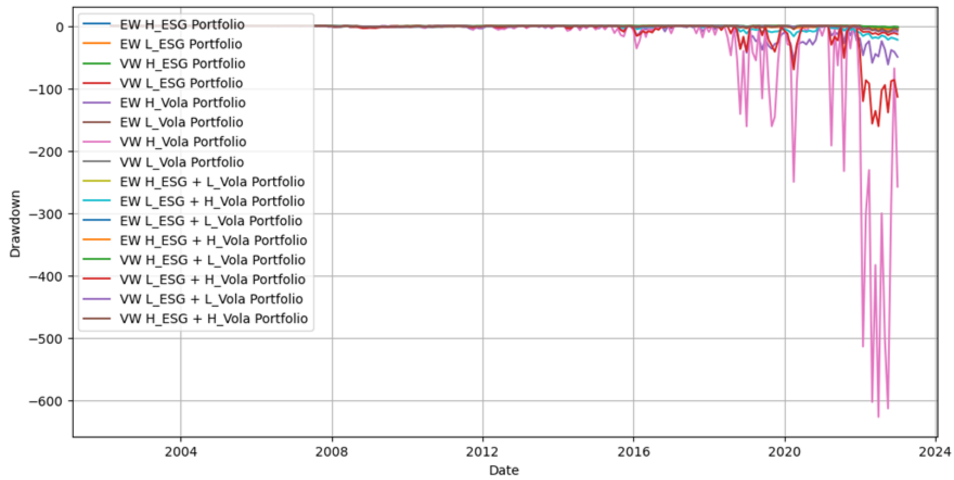

Exhibit 8: Drawdowns of all Portfolios in the In-Sample period

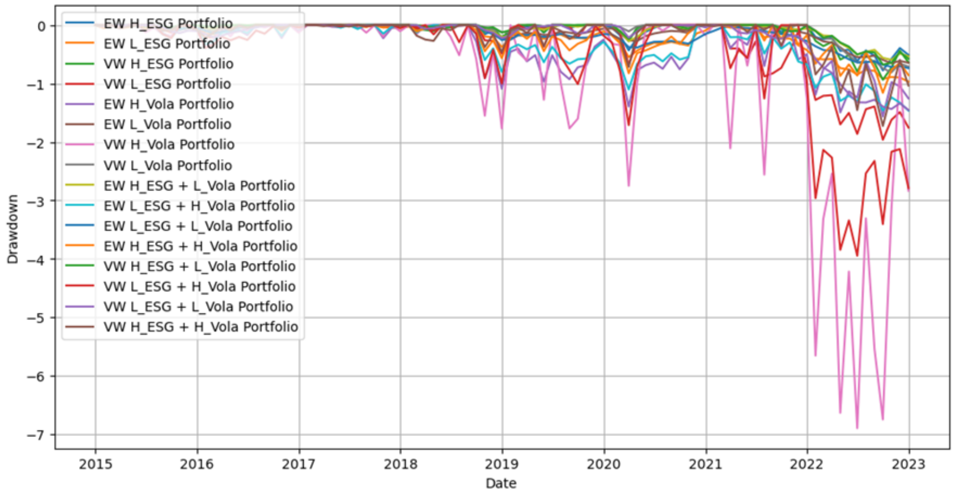

Exhibit 9: Drawdowns of all Portfolios in the Out-Sample period

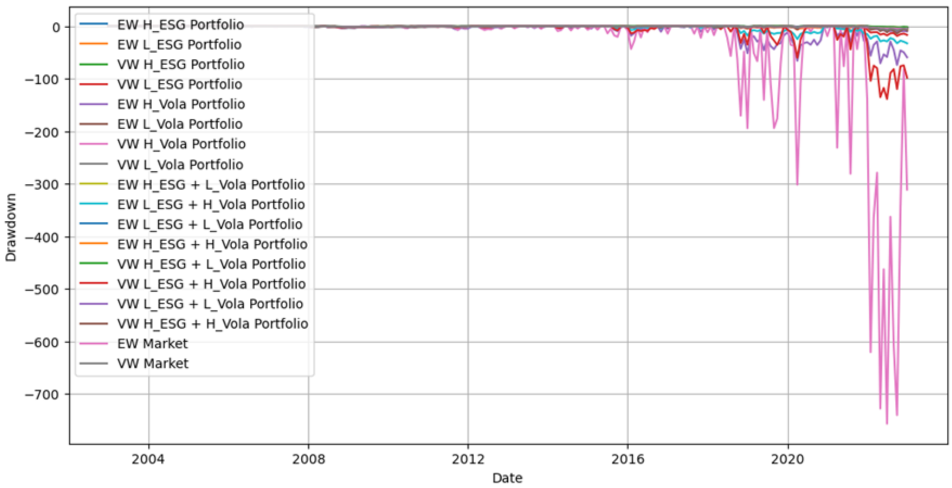

Exhibit 10: Drawdowns of all Portfolios in the Full-Sample period