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ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

UNRAVELING THE ESG LOW-VOLATILITY LINK: DO ESG PROVIDE RISK-ADJUSTED RETURNS IN EUROPEAN MARKETS

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Abstract

This paper addresses the gap in understanding the link between ESG criteria and the low-volatility signal in the European Market. Best-in-class and worst-in-class portfolios, based on ESG scores and volatility individually and subsequently on a combined strategy, consistently show that low ESG score decile stocks outperform top decile stocks in both individual and combined strategies. Both portfolios provide positive significant alphas against CAPM and FF5, with the lower ESG portfolio demonstrating superior alphas. However, conflicting results are found in the group part of the field lab, proving distinct outcomes between the United States and European markets.

Keywords: Finance, Quantitative Investing, Portfolio Construction, ESG Investing, Low-Volatility, Europe

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1. Introduction

According to the latest "Sustainability Reality" report conducted by Morgan Stanley in the First Half of 2023, sustainable funds' assets under management (AUM) continue to grow, exceeding a total of $3.1 trillion globally at the end of June 2023. The demand for sustainable funds is far from diminishing and appears to be holding steady as patient capital for investors targeting longer-term horizons. Additionally, Europe continues to far outpace every other region in terms of number of sustainable funds with a total 89% of sustainable AUM, followed by the 10% of sustainable AUM domiciled in North America.

While it is set in stone that investors are increasingly concerned with integrating ESG criteria when constructing their portfolios, the motivations behind it are highly nuanced. In a survey where European investors could pick multiple reasons for incorporating ESG criteria into their investment strategy around 56% stated a beneficial social impact, 51% want to keep up with the current market trends and 40% 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, 43% stated outperformance only 8% affirmed underperformance and whooping 54% declaring neither.

2. Literature Review

That being said, ESG investing performance appears to be a controversial topic and there are multiple approaches to its research. Firstly, qualitative studies grounded in case studies, real-life interviews, and examination of regulatory frameworks. Duong (2021) explores how integrating ESG factors on equity valuation can significantly impact a company's financial forecasts, terminal value, and risk assessment and how companies that fail to meet ESG standards may face decreased sales, increased litigation costs, and higher operational expenses, ultimately affecting their valuation.

Secondly, there are multiple quantitative, data-based research also with distinct approaches. Auer (2016), applied a negative screening approach during the period from 2004 to 2012 where stocks with poor ESG ratings are excluded from the European stock universe. The results demonstrated an increased in the mean monthly excess return of 0.11% and reducing volatility by 0.08% compared to the benchmark portfolio comprising the entire European stock sample.

Xiao et al (2013) aim to determine whether sustainability factors influence asset pricing returns. Time-series regressions are calculated for 25 global portfolios and four coefficient factors are analysed: the market factor (Mkt-rf), size (SMB), book-to-market (HML), and the sustainability factor (SUS). The majority of the portfolios had negative coefficients on the SUS factor, however only a few were statistically significant, concluding that sustainability investments do not significantly impact equity returns.

Yet, more recently, Whelan, Atz and Clark (2020) reviewed over 1000 research papers published between 2015 and 2020 showing that 58% of corporate studies show a positive relationship between ESG metrics and operational metrics such as ROE, ROA, or stock price, with only 8% conveying a negative relationship. Additionally, 59% of research focused on risk-adjusted attributes such as Alphas and Sharpe Ratios showed a similar or better performance relative to conventional investment approaches while only 14% found negative results.

The low-volatility effect is a phenomenon that during the years has puzzled and intrigued financial analysts and investors. This effect observes that over the long term, stocks with lower volatility often outperform their higher-volatility counterparts persisting in different market environments and regions. This counterintuitive performance challenges the fundamental assumptions of modern portfolio theory, which posits a direct correlation between risk and return. (Baker et al 2011).

In theory, an ESG-constrained strategy is anticipated to display lower risk-adjusted performance. By excluding companies with poor ESG scores restricts the investment universe, potentially diminishing diversification opportunities. Comparing the efficient frontier of assets with a specified ESG score threshold to one without constraints, the former is expected to lie below the latter. This deviation from the market portfolio leads to a less efficient allocation of capital and potentially lower risk-adjusted returns (Pedersen et al., 2021).

However, similarly to the lessons drawn from the low-volatility effect, the real-world application of ESG investing may reveal outcomes that diverge from theoretical predictions.

Empirical research on the United States (US) market indicates a significate positive correlation between stock ESG rating and risk-adjusted returns especially over the 2007-2012 period. This result may be related with the low-volatility effect. Chi-square frequency tests showed that high ESG stocks tend to be in the low-volatility group and low ESG stocks tend to be in the high-volatility group, in a statistically significant way in almost all time periods.

In addition, the scholars also identify a positive ESG effect, independent of the low-volatility anomaly. When looking at periods of higher market volatility, the relationship between stock volatility and ESG scores is even stronger implying that asset managers can get diversification benefits choosing ESG stocks (De and Clayman, 2015). Evidence from the COVID-19 Pandemic in 2021 for China enterprises also aligns with these implications where companies with excellent ESG performance saw a lower increase in volatility than those with poor ESG performance and rapid stabilization of stock price after this period showing once again not only a strong “resilience” of excellent ESG score stocks but also the ability to recover faster from the impact of a crisis (Yin et al, 2023).

The exploration of the intersection between ESG criteria and the low-volatility signal has been thorough in the context of the US and Chinese markets. However, a significant gap persists in the holistic study of European markets, despite Europe's leading role in embracing sustainable funds. This oversight is particularly noteworthy considering the unique characteristics and dynamics of European financial markets. Europe's robust commitment to sustainable investing, coupled with its diverse economic landscape, makes it an essential area for extending research in this domain.

3. Data

3.1 Financial Company Data

To evaluate the impact of integrating ESG considerations and the low volatility signal into an investor’s portfolio within the European Markets, a wide-ranging European Index is considered. The selected investment universe is grounded in the Refinitiv Europe Index, a free-float market capitalization-weighted index, that includes a total of 1842 companies, encompassing more than 99,5% of the investable market capitalization within European equities (Refinitiv, 2022).

The financial company specific data includes the GICS (Global Industry Classification Standard) sector and industry classification, market capitalization and monthly total return. This last one incorporates the price change difference from month t-1 to t0 while also incorporating any relevant dividends for the last month. It’s noteworthy that in order to incorporate this strategy in the group section of this field lab the currency selected was USD (United States Dollar).

To facilitate comparative analysis, the monthly returns are calculated by adjusting for the short-term risk-free rate for the Eurozone. This data is obtained from the Kenneth R. French Data Library, specifically from the Fama-French European 5 Factor database.

After accounting for inaccuracies within the data such as missing values, zero values, extreme outliers, and removing monthly returns exceeding the 990% (Schmidt et al, 2015), the investment universe is reduced to 1801 companies.

For the Market Capitalization (Table 1) there are 323239 observations. After allocating Market Cap Categories to the data set (Table 2), it is noticeable that in the last date point of the data (31/12/2022), 46.01% of the companies are Small Cap ones, followed by Mid Cap with 32.53% and Large Cap with 14.83%. The mean is significantly greater than the median, suggesting a rightwards skew in the data which persists even after the adjustments for extreme outliers.

Regarding the Monthly Returns Data (Table 1), the dataset contains 347200 entries, which is a similar yet slightly larger count compared to the observations recorded for Market Capitalization. The mean of monthly returns is approximately 1.20%, indicating that on average the returns are slightly positive. Yet, this value is slightly larger than the median, indicating that the data is right wards skewed even after adjustments for extreme outliers.

3.2 ESG Data

Unlike financial reports, ESG data can be disclosed at any time of the year in an unstructured way. This in alignment with the increasingly critical importance of transparent, accurate and comparable ESG data make it crucial to select the most reliable and comprehensive data when undertaking quantitative analysis.

In order to follow all of these aspects while also ensuring that the ESG metrics are consistent with the financial one, the data is obtained from the same source, Refinitiv.

This financial data provider offers one of the most comprehensive ESG databases in the industry, covering over 85% of the global market cap, with sufficient ESG score coverage from 2002 onwards, updated on a weekly bias (Refinitiv, 2022).

The number of observations of the ESG data (Table 3) is fewer than the ones of the financial data counting with 16947 observations also due to the yearly frequent nature of the data. The mean value (54.19) is really similar to the median value (55.78) suggesting that there are no outliers and the data is normally distributed. When adjusting the data to the Refinitiv ESG Grades (Table 4), it is noticeable that in the last date point of the data (31/12/2022), 52.12% of the companies have a B rating, followed by 27.75% of a A rating and 18.21% having a C rating. 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.

3.3 Data Merge

Following the consolidation of both Financial and ESG data the volatility values with a 1-month lag were computed, both missing values, zero values and duplicates were accounted for, and in order to create deciles dates with less than 10 investable companies were neglected resulting in a dataset of a total of 1480 investable companies.

The largest fraction is listed (Table 6) in the United Kingdom (18.89%), followed by Sweden (13.28%), Germany (10.11%) and France (8.92%). Regarding the represented sectors (Table 7), the majority of the companies are linked to the Industrials sector (22.89%), followed by the Financials sector (15.13%), Consumer Discretionary (12.41%) and finally Healthcare (8.03%).

4. Methodology

To conduct the empirical analysis, distinct time intervals are defined. The period used for in-sample analysis spans from December 2002 to December 2014, while the out-sample encompasses the timeframe from December 2014 to December 2022.

For these two timeframes, best-in-class and worst-in-class portfolios are created by arranging all investable assets at according to their ESG score. A similar approach is applied to the volatility of the assets. The top decile of the ESG ranking is composed of the best ESG score companies within each timeframe and classified as H_ESG, whereas the lowest ESG score companies are classified as L_ESG.

Similarly, the top decile of the Volatility ranking has the companies with the highest volatility H_Vola, while the lowest one is composed of the lowest volatility companies, L_Vola. Based on the results of the individual signals, a combined ranking is created by integrating equally the ESG and Volatility ranking. The four pairwise combinations of ESG criteria and Volatility (L_ESG + H_Vola; L_ESG + L_Vola; H_ESG + H_Vola; H_ESG + L_Vola) are tested. Equal-Weighted (EW) and Value-Weighted (VW) Portfolios were created having a total of 16 portfolios in each sample period.

Additionally, two Market Portfolios are created consisting on an equal-weighted and value-weighted portfolio composing all the investable assets independently of their ESG score or volatility. This will function as a benchmark for evaluating the effectiveness of ESG-focused or volatility-based portfolios providing a standard against which their performance can be measured.

Following the portfolio construction, performance indicators such as Annualized Excess Returns, Annualized Standard Deviation, Annualized Sharpe Ratios and Drawdowns were calculated for each portfolio to ensure risk-adjusted performance could be evaluated. To facilitate the comparison within portfolios and investigate their behaviours in economic periods with higher volatility, the cumulative returns are also plotted against each other.

Finally, the two best portfolios of the in-sample period are exposed to the Capital Asset Pricing Model (CAPM) and Fama-French Five-Factor (FF5) in order to analyse how sensitive the portfolios are to market movements and identify anomalous returns.

5. Results

5.1. In-Sample Results

5.1.1. Results of the individual ESG score strategy

In the case of both Equal-Weighted and Value-Weighted portfolios focusing solely on ESG scores (Table 9), portfolios within the L_ESG group consistently yield higher returns compared to their H_ESG counterparts. This trend persists when evaluating performance using risk-adjusted measures like the Sharpe Ratio. In fact, the H_ESG portfolios have lower annualized returns for similar values of annualized volatility than the respective market portfolios (Table 10) and L_ESG counterparts challenging the notion that a higher ESG rating translates to lower volatility.

Table 9: Performance Stats of ESG only Portfolios and Benchmark

Portfolio		Annualized Return	Annualized Volatility	Sharpe Ratio
EW H_ESG	Full-Sample	7.42%	17.91%	0.415
	In-Sample	8.98%	17.38%	0.516
	Out-Sample	8.99%	17.29%	0.520
EW L_ESG	Full-Sample	15.92%	18.51%	0.860

	In-Sample	16.47%	18.39%	0.895
	Out-Sample	18.99%	17.26%	1.100
VW H_ESG	Full-Sample	8.26%	16.02%	0.516
	In-Sample	10.01%	15.38%	0.651
	Out-Sample	9.72%	14.44%	0.673
VW L_ESG	Full-Sample	17.39%	17.96%	0.968
	In-Sample	17.53%	16.64%	1.053
	Out-Sample	19.64%	17.32%	1.134

A preliminary observation of the cumulative growth pattern of 1 USD invested in Value-Weighted Portfolios during the 2008 financial crisis (Graph 13) suggests that the H_ESG portfolio might have experienced lower volatility. Focusing on the confined time frame from December 2006 to December 2010 (Table 14), the H_ESG portfolio shows in fact lower volatility 20.28%, compared to its counterpart 22.58%. However, the Sharpe Ratio of the L_ESG is superior 0.304 compared to 0.278 and a subsequent t-test reveals that this observed difference in volatility lacks statistical significance.

5.1.2. Results of the individual Volatility strategy

For the Equal-Weighted portfolios focused on Volatility (Table 10), the commonly referenced low-volatility anomaly is not observed. The Sharpe ratios for the H_Vola and L_Vola portfolios are relatively close, with the H_Vola portfolio holding a Sharpe Ratio of 0.840 and the L_Vola portfolio just slightly lower at 0.801. This proximity in Sharpe ratios suggests that despite different volatility levels, the risk-adjusted performance of both portfolios is comparable.

Turning to the Value-Weighted portfolios, the low-volatility anomaly becomes evident. The L_Vola outperforms, as demonstrated by a 0.35-point difference in the Sharpe Ratio (1.033) compared to the H_Vola (0.683). Furthermore, the L_Vola portfolio surpasses the market's risk-adjusted returns by 0.214 points in the Sharpe ratio, highlighting its outperformance against the benchmark.

5.1.3. Results of the combined Strategy

The incorporation of the Low-Volatility signal into ESG portfolios (Table 11) has naturally beneficiated results across the board, reducing the annualized volatility for all the portfolios. In the Equally Weighted Portfolios the biggest reduction in annualized volatility occurs in the H_ESG portfolio which decreases 6.34% compared to the 5.76% reduction in the L_ESG. The similar happens in the Value-Weighted Portfolios where the Low-Volatility signal reduces the annualized volatility of the H_ESG portfolio by 5.74% compared to the 5.01% less in the L_ESG. Despite these variations, both portfolios maintain closely aligned values for annualized volatility, differing by a maximum of 1.39% in the VW portfolios. Reiterating the idea than a higher ESG rating doesn't necesairly provide lower volatility.

Table 11: Performance Stats of Combined Portfolios

Portfolio		Annualized Return	Annualized Volatility	Sharpe Ratio
EW H_ESG + L_Vola	Full-Sample	6.33%	11.33%	0.559
	In-Sample	8.35%	11.04%	0.756
	Out-Sample	6.59%	10.70%	0.616
EW L_ESG + L_Vola	Full-Sample	7.71%	12.20%	0.633
	In-Sample	10.17%	12.64%	0.805
	Out-Sample	8.13%	10.70%	0.760
VW H_ESG + L_Vola	Full-Sample	7.29%	10.57%	0.689
	In-Sample	8.86%	9.64%	0.919
	Out-Sample	8.67%	10.48%	0.827
VW L_ESG + L_Vola	Full-Sample	11.06%	11.96%	0.924
	In-Sample	13.26%	11.64%	1.140
	Out-Sample	11.84%	11.69%	1.013

The integration of the Low-Volatility signal also positively influences the Sharp ratios of all the portfolios apart from the EW L_ESG portfolio. The greatest difference is once again seen in the EW and VW H_ESG portfolios that respectively increase their Sharpe Ratio by 0.240 and 0.268 points.

Revisiting the 2008 financial crisis period, from December 2006 to December 2010, once again (Table 12) it is clear that the H_ESG portfolio provides a lower volatility of 12.41% compared to 14.31%. Yet, this difference isn't considered statistically significant and the Sharpe Ratio of the L_ESG (0.446) continues to surpass the H_ESG (0.116).

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 value of 1.140. This suggests that investors prioritizing risk-adjusted returns would find this portfolio more attractive.

5.1.4. CAPM and FF5 exposure

When putting the best performance portfolio (Table 13), VW L_ESG + L_Vola, against the CAPM a significant (0.000 p-value) positive alpha of 0.79% is found indicating that the combined signal generates positive excess returns beyond what can be explained by its exposure to market risk. The portfolio has a statistically significant beta of 40.03% (0.000 p-value), indicating that it tends to move with less magnitude than the market.

Table 13: CAPM Regression results

Portfolio	Period	Alpha	P-Value	IR
VW L_ESG + L_Vola	Full-Sample	0.81%	0.002	0.32
	In-Sample	0.79%	0.000	0.31
	Out-Sample	0.81%	0.002	0.32
VW H_ESG + L_Vola	Full-Sample	0.54%	0.011	0.26
	In-Sample	0.46%	0.006	0.23
	Out-Sample	0.54%	0.011	0.26

When adding the exposure of size, value, profitability, and investment through the FF5 model (Table 14), a slightly lower significant (0.002 p-value) value of 0.72% is found for the alpha. The second-best portfolio, VW H_ESG + L_Vola, indicates and a lower positive significant (0.006 p-value) alpha of 0.46% for the CAPM and a 35.56% significant (0.000 p-value) beta.

Table 14: FF5 Regression results

Portfolio	Period	Alpha	P-Value	IR
VW L_ESG + L_Vola	Full-Sample	0.67%	0.000	0.28
	In-Sample	0.72%	0.002	0.30
	Out-Sample	0.65%	0.013	0.27
VW H_ESG + L_Vola	Full-Sample	0.40%	0.007	0.18
	In-Sample	0.36%	0.054	0.18
	Out-Sample	0.57%	0.012	0.27

5.2. Out-Sample Results

5.2.1. Results of the individual ESG score strategy

The results in the out-sample period for the individual ESG score strategies follow what is seen in the in-sample period (Table 1). The L_ESG portfolios continue to yield higher returns compared to their H_ESG counterparts and this trend persists in the Sharpe Ratios of the portfolios. While the H_ESG experience very similar results in annualized returns and Sharpe Ratio compared to the in-sample period the L_ESG portfolios experience a slight increase in Sharpe Ratio of 0.204 and 0.076 respectively for Equally-Weighted and Value-Weighted. One interesting thing to note however, is that the VW_H_ESG Portfolio experiences significant lower volatility (14.44%) than the other portfolios suggesting that in this period larger companies with H_ESG scores exhibit less volatility.

5.2.2. Results of the individual Volatility strategy

The Volatility Signal Portfolios also follow the results seen in the in-sample period proving the persistence of the low-volatility anomaly in the Value-Weighted Portfolios.

5.2.3. Results of the combined Strategy

The integration of the Low-Volatility Signal continues to beneficiate positively annualized volatility and Sharpe Ratios. When looking at the Equally-Weighted Portfolios the incorporation of the volatility signal seems to influence the portfolios equally with a decrease of 6,59% of volatility in H_ESG and 6,56% in L_ESG. However, the opposite happens to the Value-Weighted Portfolios where the volatility of H_ESG only decreases 3,95% compared to a whopping 5,63% in L_ESG. This reinforces that larger companies within the H_ESG group might present overall lower volatility. Despite this interesting observation, the portfolio with the highest Sharpe Ratio remains the VW L_ESG + L_Vola Portfolio boasting 1.013 which outperforms the VW H_ESG + L_Vola portfolio with 0.827 of Sharpe Ratio.

5.2.4. CAPM and FF5 exposure

When evaluating the performance of the VW L_ESG + L_Vola and VW H_ESG + L_Vola against the CAPM and FF5 (Table 13 & 14) the VW L_ESG + L_Vola consistently provides higher significant alphas, 0.81% (0.002 p-value) for the CAPM and 0.57% (0.012 p-value) for the FF5 compared to the VW H_ESG + L_Vola that exhibits an alpha of 0.54% (0.011 p-value) and 0.57% (0.012 p-value), respectively.

6. Limitations

There are a couple of potential shortcomings regarding the broad applicability of the empirical analysis conducted in this paper. The emergent nature of ESG factors in finance results in a scarcity of extensive historical data especially in the first years of the chosen sample. To address this challenge, future studies could reanalyse the current dataset, incorporating ESG scores from alternative sources. The distribution of ESG factor data is also uneven across different industries meaning that not all industries are equally represented in the analysis. Additionally, despite Refinitiv claims to have minimized the size bias within ESG factor data, there is still an observable tendency for larger companies to possess higher ESG ratings, as evidenced by the persistent and even increased magnitude of size bias in the Refinitiv ESG data across various size proxies (Dobrick et all, 2023). Within portfolio construction, the decile-based methodology effectively differentiates stocks into distinct H_ESG and L_ESG categories. Nonetheless, this approach may result in portfolios of limited size and diversity and affect the representativeness of the results. Finally, given that the portfolio undergoes monthly rebalancing based on both ESG and volatility data, investors are likely to encounter significant transaction costs rendering the real-world application of this approach. To mitigate this issue, one solution would be to reduce the transaction frequency or even integrate predictive models to anticipate changes in ESG and volatility.

7. Conclusion

In the individual segment of this field-lab, an in-depth analysis was conducted on the European Market, examining ESG Scores and Low-Volatility Signal strategies as well as the combination of the two. It was consistently observed that the portfolios comprised of low ESG score decile stocks and low volatility outperformed those composed by the high ESG score decile and low volatility in terms of risk-adjusted returns. When holding the portfolio's returns against benchmark models, CAPM and FF5, both yield positive and significant alphas indicating their effectiveness in generating excess returns over the expected returns of the market. Yet, the L_ESG + L_Vola portfolio consistently exhibited higher alphas than the H_ESG + L_Vola portfolio.

The integration of the Low-Volatility Signal appears to have a more pronounced influence on the H_ESG portfolios. Yet, both the ESG only portfolios and combined strategies exhibit very similar values of annualized volatility for all the sample periods challenging the belief that higher ESG rated companies generally provide lower volatility, in contrast to prior research on the US market. During the 2008 financial crises, the H_ESG + L_Vola strategy exhibited lower volatility for the same annualized return as its counterpart. However, it's crucial to note that the observed difference lacked statistical significance. In light of these insight, further research and exploration are warranted to delve deeper into the intricate dynamics of ESG and low-volatility interactions in the European market.

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II. Appendix

Table 1: Summary Statistics of financial company Data

	Monthly Return	Market Capitalization (in million USD)
Number of Observations	347200	323239
Mean	1.20%	8,725.755
Standard Deviation	11.14%	28,456.25
Minimum	-98.56%	0.032007
1st Quartile	-4.47%	486.3772
2nd Quartile	0.77%	1,645.478
3rd Quartile	6.33%	5,776.317
Maximum	98.92%	807,173.0

Table 2: Market Cap information on 31 December 2022

	Number of Observations	Percentage
Nano Cap	1	0.06%
Micro Cap	91	5.11%
Small Cap	819	46.01%
Mid Cap	579	32.53%
Large Cap	264	14.83%
Mega Cap	26	1.46%

Table 3: Summary Statistics of ESG Data

	ESG Scores
Number of Observations	16947
Mean	54.19
Standard Deviation	20.42
Minimum	0.63
1st Quartile	39.40
2nd Quartile	55.78
3rd Quartile	70.44
Maximum	95.91

Table 4: ESG Grade information on 31 December 2022

	Number of Observations	Percentage
A	419	27.75%
B	787	52.12%
C	275	18.21%
D	29	1.92%

Table 5: Annual ESG Score Mean and Number of Observations

Year	Number of Observations ESG	ESG mean
2001	10	37.27
2002	234	38.03
2003	296	38.21
2004	397	38.00
2005	507	38.70
2006	540	39.63
2007	578	43.59
2008	613	47.74
2009	641	50.21
2010	670	51.76
2011	697	52.49
2012	716	53.24
2013	729	53.57
2014	751	53.98
2015	800	55.28
2016	822	56.98
2017	894	58.00
2018	1175	56.40
2019	1333	57.10
2020	1468	59.51
2021	1527	62.16
2022	1549	63.54

Table 6: Countries of Exchanges Distribution

Exchange Country	Total	Percentage
United Kingdom	286	18.89%
Sweden	201	13.28%
Germany	153	10.11%
France	135	8.92%
Switzerland	104	6.87%
Italy	99	6.54%
Turkey	83	5.48%
Norway	80	5.28%
Spain	61	4.03%
Finland	51	3.37%
Netherlands	47	3.10%
Denmark	45	2.97%
Belgium	44	2.91%
Poland	38	2.51%
Austria	27	1.78%
Greece	23	1.52%
Republic of Ireland	15	0.99%
Portugal	14	0.92%
Hungary	5	0.33%
Czech Republic	3	0.20%

Table 7: GICS Sector Distribution

GICS Sector Name	Total	Percentage
Industrials	345	22.89%
Financials	228	15.13%
Consumer Discretionary	187	12.41%
Health Care	121	8.03%
Materials	119	7.90%
Information Technology	114	7.56%
Real Estate	94	6.24%
Consumer Staples	93	6.17%
Communication Services	82	5.44%
Utilities	66	4.38%
Energy	58	3.85%

Table 8: GICS Industry Distribution

GICS Industry Name	Total	Percentage
Machinery	82	5.42%
Banks	82	5.42%
Capital Markets	61	4.03%
Real Estate Management & Development	48	3.17%
Chemicals	47	3.10%
Insurance	44	2.91%
Construction & Engineering	41	2.71%
Oil, Gas & Consumable Fuels	40	2.64%
Specialty Retail	40	2.64%
Hotels, Restaurants & Leisure	39	2.58%
Food Products	38	2.51%
Financial Services	36	2.38%
Metals & Mining	34	2.25%
Electronic Equipment, Instruments & Components	32	2.11%
IT Services	31	2.05%
Pharmaceuticals	31	2.05%
Media	29	1.92%
Health Care Equipment & Supplies	29	1.92%
Electrical Equipment	28	1.85%
Household Durables	27	1.78%
Professional Services	27	1.78%
Commercial Services & Supplies	27	1.78%
Building Products	25	1.65%
Software	24	1.59%
Textiles, Apparel & Luxury Goods	24	1.59%
Consumer Staples Distribution & Retail	23	1.52%
Diversified Telecommunication Services	23	1.52%
Trading Companies & Distributors	23	1.52%
Biotechnology	23	1.52%
Aerospace & Defense	23	1.52%
Independent Power and Renewable Electricity Producers	22	1.45%
Electric Utilities	22	1.45%
Industrial Conglomerates	21	1.39%
Automobile Components	21	1.39%
Semiconductors & Semiconductor Equipment	20	1.32%
Energy Equipment & Services	18	1.19%
Life Sciences Tools & Services	17	1.12%
Construction Materials	17	1.12%
Beverages	17	1.12%
Health Care Providers & Services	15	0.99%

Automobiles	15	0.99%
Entertainment	13	0.86%
Passenger Airlines	13	0.86%
Air Freight & Logistics	12	0.79%
Multi-Utilities	11	0.73%
Containers & Packaging	11	0.73%
Paper & Forest Products	11	0.73%
Retail REITs	10	0.66%
Personal Care Products	10	0.66%
Broadline Retail	10	0.66%
Interactive Media & Services	10	0.66%
Marine Transportation	10	0.66%
Diversified REITs	9	0.59%
Office REITs	8	0.53%
Transportation Infrastructure	8	0.53%
Leisure Products	7	0.46%
Gas Utilities	7	0.46%
Industrial REITs	7	0.46%
Consumer Finance	7	0.46%
Wireless Telecommunication Services	7	0.46%
Health Care Technology	6	0.40%
Ground Transportation	6	0.40%
Residential REITs	5	0.33%
Communications Equipment	4	0.26%
Diversified Consumer Services	4	0.26%
Water Utilities	4	0.26%
Health Care REITs	4	0.26%
Technology Hardware, Storage & Peripherals	3	0.20%
Tobacco	3	0.20%
Household Products	3	0.20%
Distributors	2	0.13%
Specialized REITs	2	0.13%
Hotel & Resort REITs	1	0.07%

Table 10: Performance Stats of all Portfolios

Portfolio	Period	Annualized Return	Annualized Volatility	Sharpe Ratio
EW H_ESG	Full-Sample	7.42%	17.91%	0.415
	In-Sample	8.98%	17.38%	0.516
	Out-Sample	8.99%	17.29%	0.520
EW L_ESG	Full-Sample	15.92%	18.51%	0.860
	In-Sample	16.47%	18.39%	0.895
	Out-Sample	18.99%	17.26%	1.100
VW H_ESG	Full-Sample	8.26%	16.02%	0.516
	In-Sample	10.01%	15.38%	0.651
	Out-Sample	9.72%	14.44%	0.673
VW L_ESG	Full-Sample	17.39%	17.96%	0.968
	In-Sample	17.53%	16.64%	1.053
	Out-Sample	19.64%	17.32%	1.134
EW H_Vola	Full-Sample	34.03%	43.77%	0.777
	In-Sample	36.00%	42.41%	0.849
	Out-Sample	30.70%	41.59%	0.738
EW L_Vola	Full-Sample	7.11%	11.25%	0.632
	In-Sample	9.37%	11.70%	0.801
	Out-Sample	6.81%	10.01%	0.680
VW H_Vola	Full-Sample	31.74%	44.96%	0.706
	In-Sample	29.10%	42.60%	0.683
	Out-Sample	33.32%	44.84%	0.743
VW L_Vola	Full-Sample	9.12%	10.43%	0.874
	In-Sample	10.08%	9.75%	1.033
	Out-Sample	10.12%	10.31%	0.982
EW H_ESG + L_Vola	Full-Sample	6.33%	11.33%	0.559
	In-Sample	8.35%	11.04%	0.756
	Out-Sample	6.59%	10.70%	0.616
EW L_ESG + L_Vola	Full-Sample	7.71%	12.20%	0.633
	In-Sample	10.17%	12.64%	0.805
	Out-Sample	8.13%	10.70%	0.760

VW H_ESG + L_Vola	Full-Sample	7.29%	10.57%	0.689
	In-Sample	8.86%	9.64%	0.919
	Out-Sample	8.67%	10.48%	0.827
VW L_ESG + L_Vola	Full-Sample	11.06%	11.96%	0.924
	In-Sample	13.26%	11.64%	1.140
	Out-Sample	11.84%	11.69%	1.013
EW L_ESG + H_Vola	Full-Sample	28.40%	33.01%	0.860
	In-Sample	31.06%	32.87%	0.945
	Out-Sample	27.23%	31.55%	0.863
EW H_ESG + H_Vola	Full-Sample	14.77%	32.90%	0.449
	In-Sample	16.65%	31.64%	0.526
	Out-Sample	14.16%	31.38%	0.451
VW L_ESG + H_Vola	Full-Sample	28.45%	33.32%	0.854
	In-Sample	30.39%	32.08%	0.947
	Out-Sample	28.04%	33.05%	0.848
VW H_ESG + H_Vola	Full-Sample	14.74%	29.59%	0.498
	In-Sample	15.65%	28.40%	0.551
	Out-Sample	16.25%	27.36%	0.594
EW Market	Full-Sample	11.61%	18.13%	0.640
	In-Sample	13.81%	17.83%	0.775
	Out-Sample	10.97%	17.38%	0.631
VW Market	Full-Sample	10.74%	15.82%	0.679
	In-Sample	12.33%	15.05%	0.819
	Out-Sample	11.95%	14.72%	0.811

Table 12: Performance Stats of Portfolios during the 2008 financial crises

Portfolio	Annualized Return	Annualized Volatility	Sharpe Ratio
VW H_ESG	5.63%	20.28%	0.278
VW L_ESG	6.87%	22.58%	0.304
VW H_ESG + L_Vola	1.44%	12.41%	0.116
VW L_ESG + L_Vola	6.38%	14.31%	0.446

Table 15: CAPM Regression Information for the VW L_ESG + L_Vola Portfolio

	CAPM		
VW L_ESG + L_Vola Portfolio	**In-Sample**	**Out -Sample**	**Full-Sample**
Alpha	0.79%	0.81%	0.67%
Alpha T-value	3.730	3.146	4.143
Alpha P-value	0.000	0.002	0.000
MktRf beta	40.03%	46.09%	43.15%
MktRf T-value	10.679	8.849	14.367
MktRf P-value	0.000	0.000	0.000
IR	0.313	0.320	0.262
R^2	44.37%	45.18%	45.22%

Table 16: CAPM Regression Information for the VW H_ESG + L_Vola Portfolio

	CAPM		
VW H_ESG + L_Vola Portfolio	**In-Sample**	**Out -Sample**	**Full-Sample**
Alpha	0.46%	0.54%	0.38%
Alpha T-value	2.778	2.595	2.736
Alpha P-value	0.006	0.011	0.007
MktRf beta	35.56%	45.25%	39.82%
MktRf T-value	12.196	10.602	15.607
MktRf P-value	0.000	0.000	0.000
IR	0.233	0.264	0.173
R^2	50.99%	54.20%	49.35%

Table 17: FF5 Regression Information for the VW L_ESG + L_Vola Portfolio

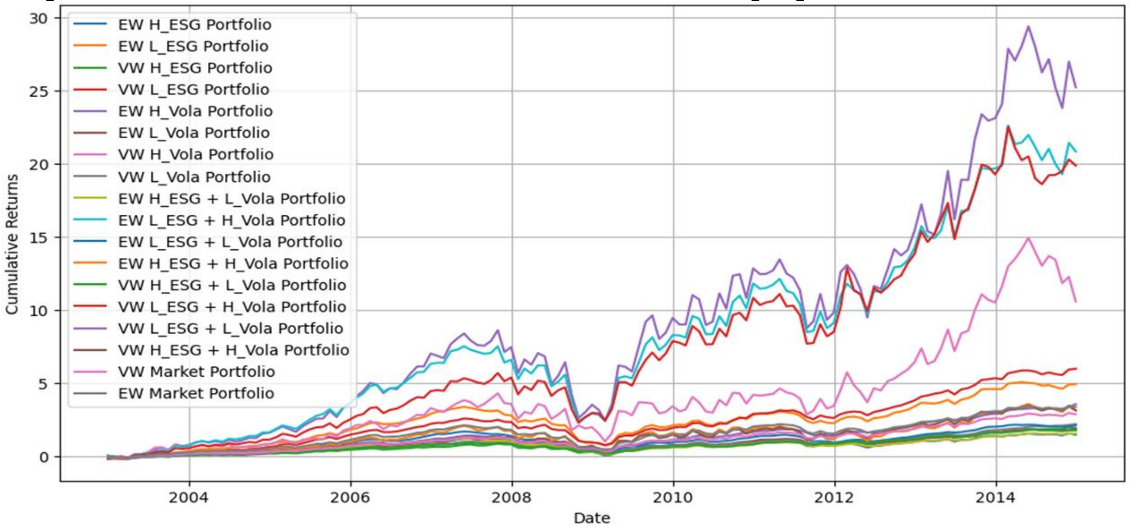
	FF5		
VW L_ESG + L_Vola Portfolio	**In-Sample**	**Out -Sample**	**Full-Sample**
Alpha	0.72%	0.65%	0.67%
Alpha T-value	3.174	2.538	4.133
Alpha P-value	0.002	0.013	0.000
MktRf beta	39.90%	39.82%	42.36%
MktRf T-value	8.260	6.404	12.160
MktRf P-value	0.000	0.000	0.000
SMB beta	43.00%	24.22%	38.17%
SMB T-value	3.982	1.458	4.552
SMB P-value	0.000	0.148	0.000
HML beta	-4.00%	8.83%	-13.19%
HML T-value	-0.266	0.451	-1.335
HML P-value	0.791	0.653	0.183
RMW beta	-2.45%	14.85%	-12.54%

RMW T-value	-0.116	0.579	-0.983
RMW P-value	0.908	0.564	0.326
CMA beta	-19.06%	-47.52%	-25.24%
CMA T-value	-1.090	-1.586	-1.892
CMA P-value	0.277	0.116	0.060
IR	0.302	0.271	0.279
R^2	51.16%	52.48%	52.29%

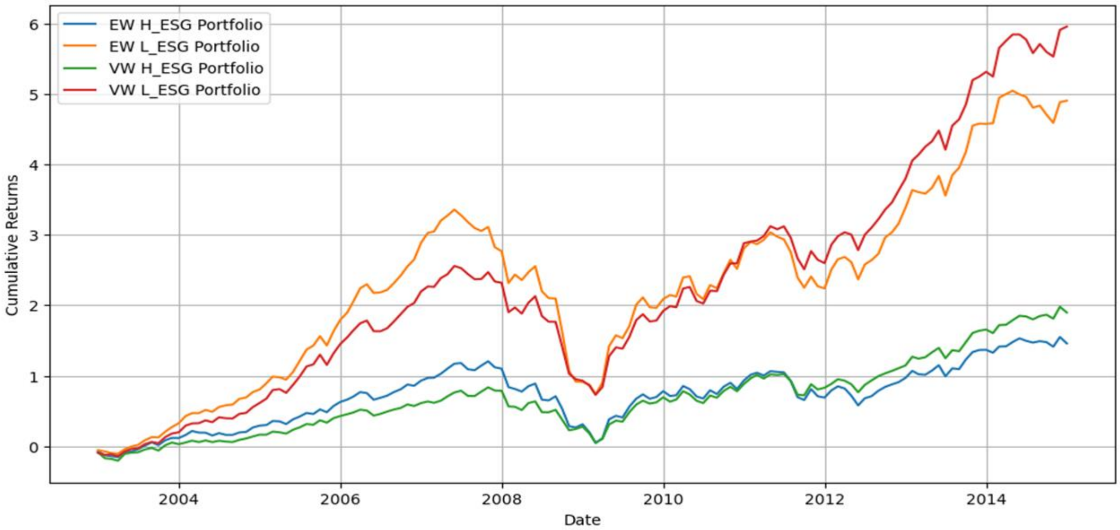
Table 18: FF5 Regression Information for the VW H_ESG + L_Vola Portfolio

	FF5		
VW H_ESG + L_Vola Portfolio	**In-Sample**	**Out -Sample**	**Full-Sample**
Alpha	0.36%	0.57%	0.40%
Alpha T-value	1.944	2.574	2.726
Alpha P-value	0.054	0.012	0.007
MktRf beta	32.76%	46.96%	37.44%
MktRf T-value	8.353	8.709	11.866
MktRf P-value	0.000	0.000	0.000
SMB beta	6.55%	-12.88%	-2.31%
SMB T-value	0.747	-0.894	-0.304
SMB P-value	0.456	0.374	0.762
HML beta	25.17%	3.00%	7.53%
HML T-value	2.064	0.177	0.841
HML P-value	0.041	0.860	0.401
RMW beta	24.99%	7.88%	-0.06%
RMW T-value	1.463	0.354	-0.005
RMW P-value	0.146	0.724	0.996
CMA beta	-15.37%	12.93%	-18.85%
CMA T-value	-1.084	0.498	-1.560
CMA P-value	0.280	0.620	0.120
IR	0.185	0.274	0.184
R^2	53.12%	55.53%	49.85%

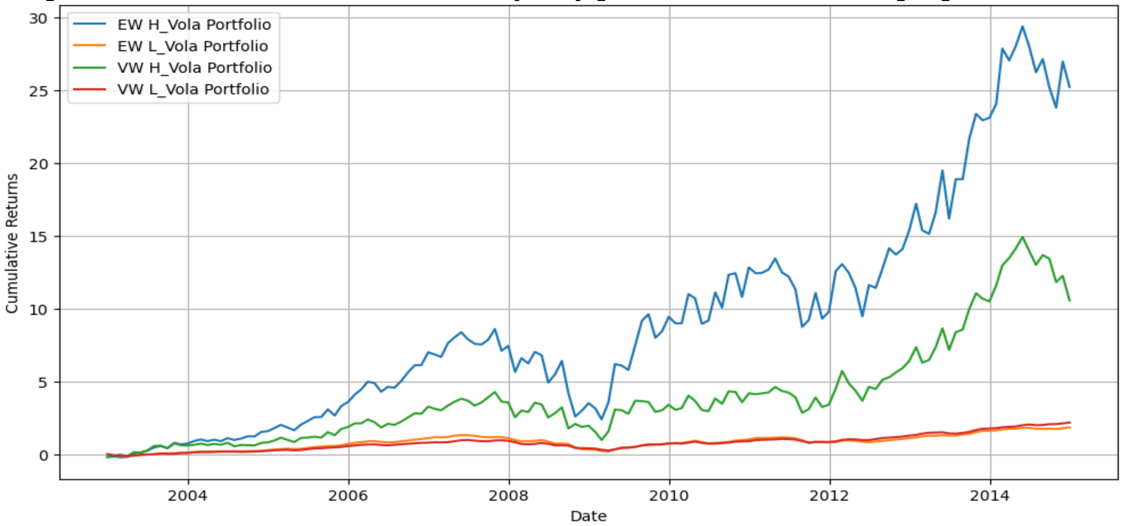
Graph 1: Cumulative Returns of all Portfolios in the In-Sample period



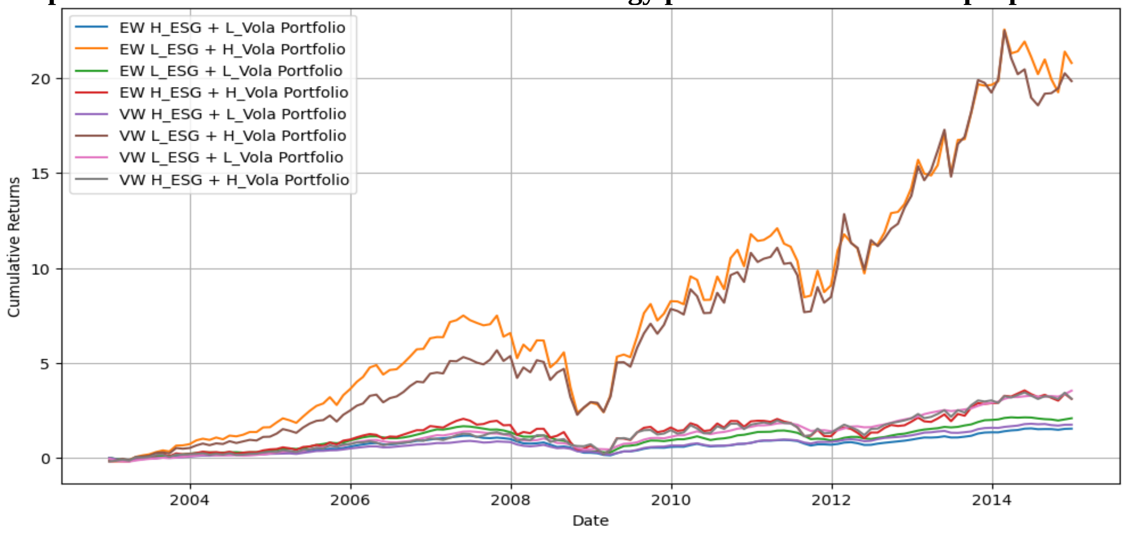
Graph 2: Cumulative Returns of ESG only portfolios in the In-Sample period



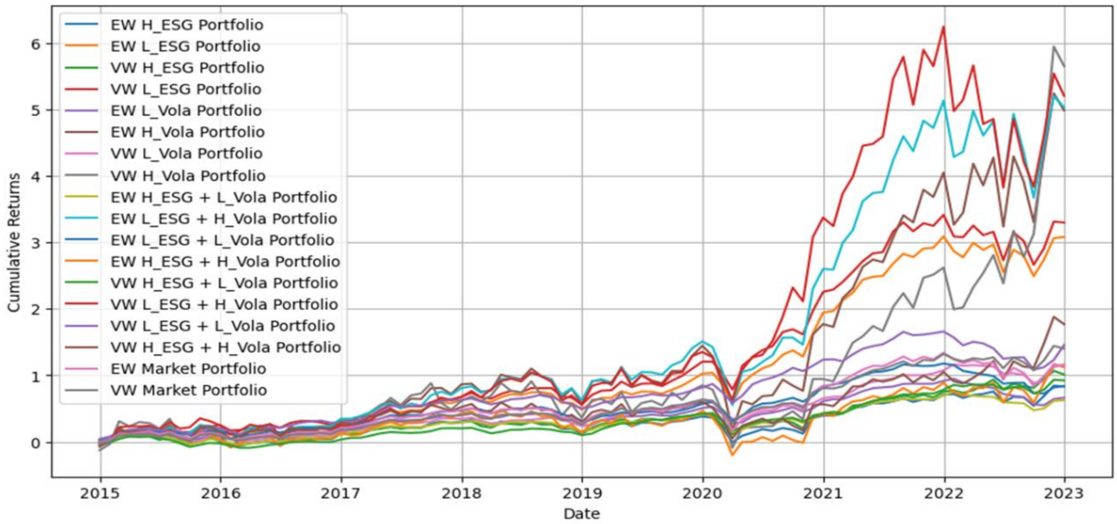
Graph 3: Cumulative Returns of Volatility only portfolios in the In-Sample period



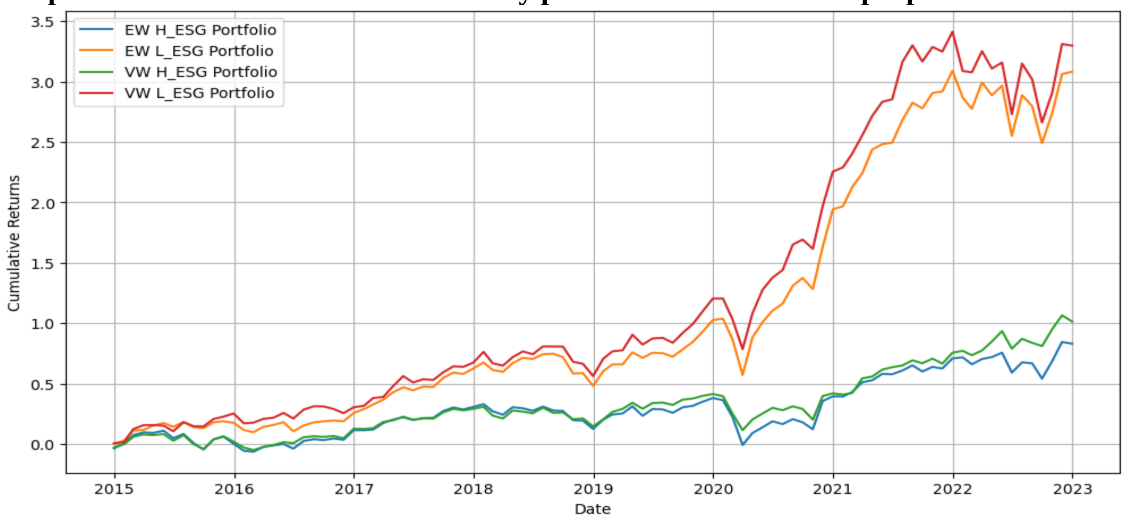
Graph 4: Cumulative Returns of Combined Strategy portfolios in the In-Sample period



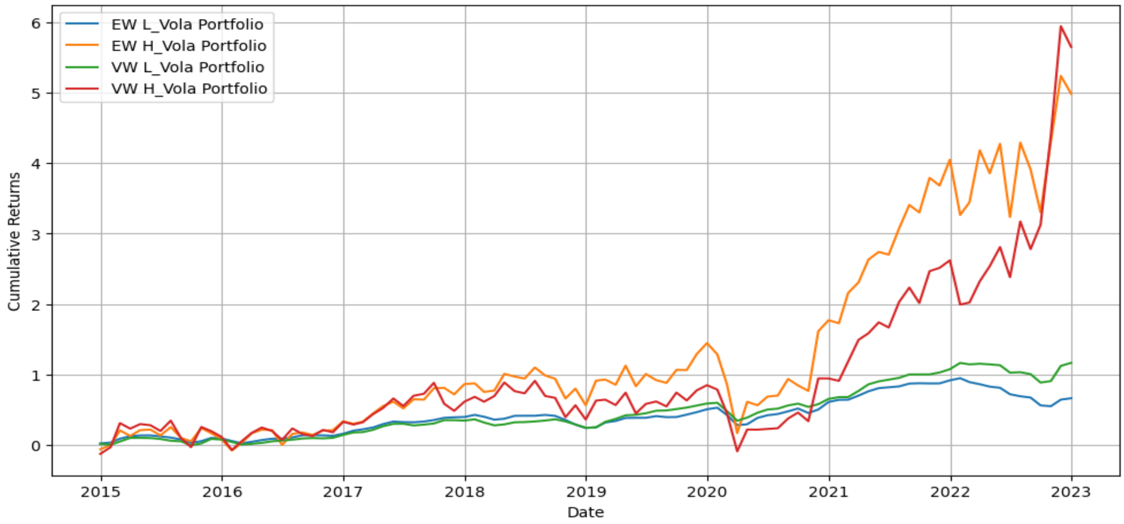
Graph 5: Cumulative Returns of all Portfolios in the Out-Sample period



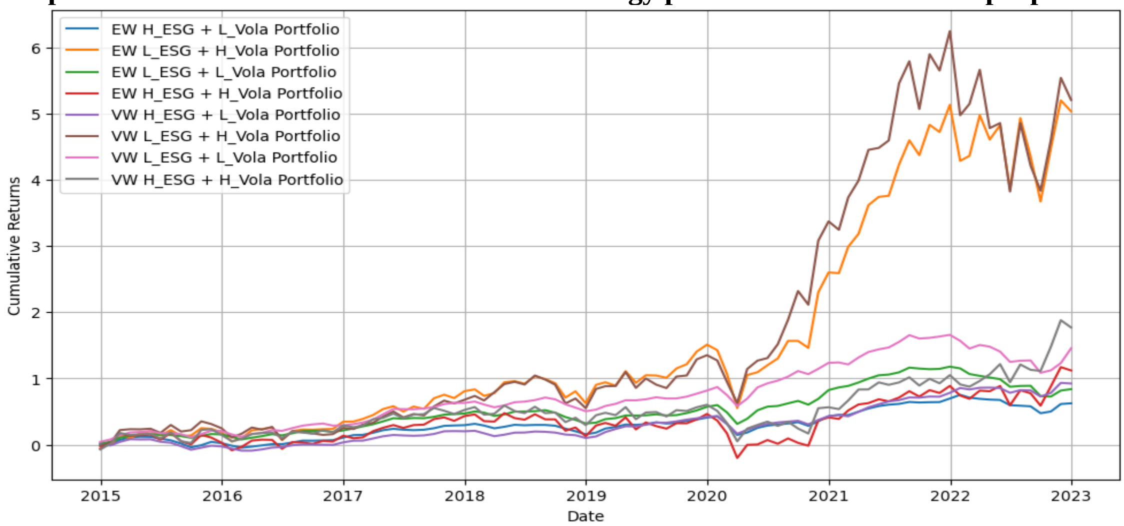
Graph 6: Cumulative Returns of ESG only portfolios in the Out-Sample period



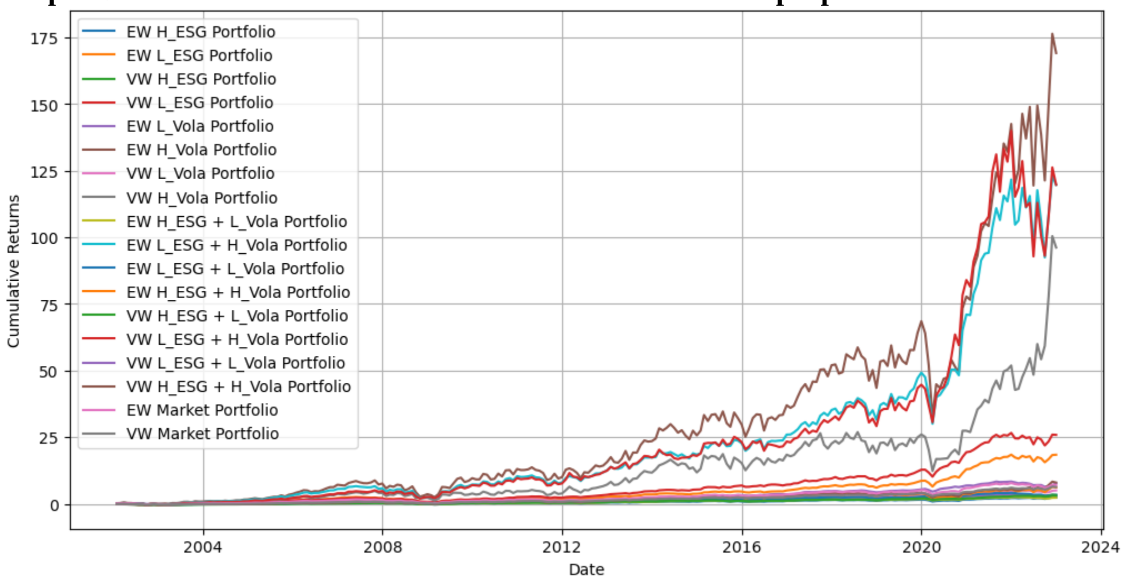
Graph 7: Cumulative Returns of Volatility only portfolios in the Out-Sample period



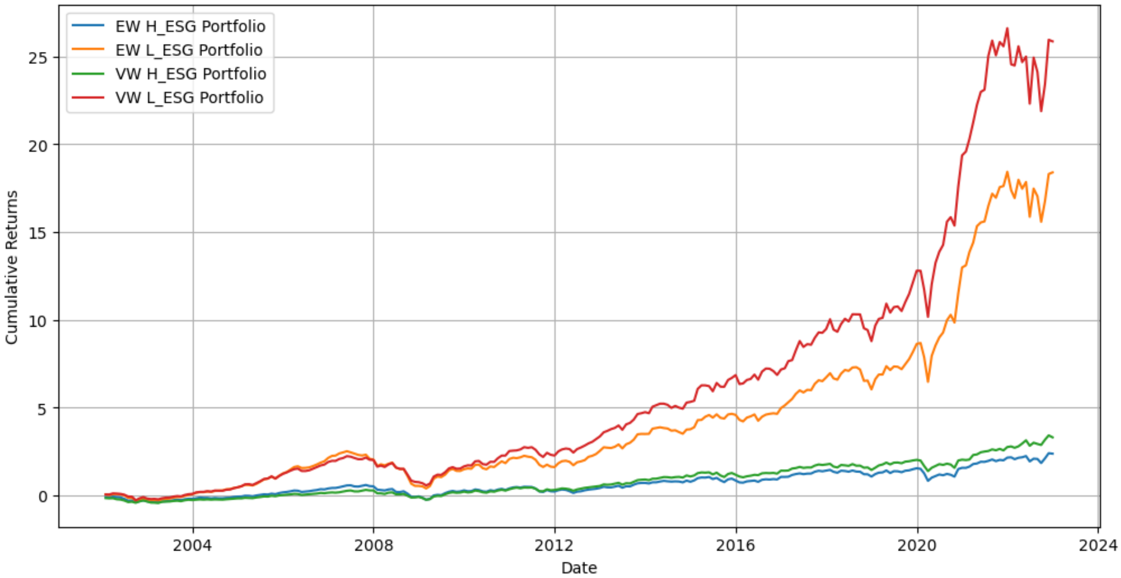
Graph 8: Cumulative Returns of Combined Strategy portfolios in the Out-Sample period



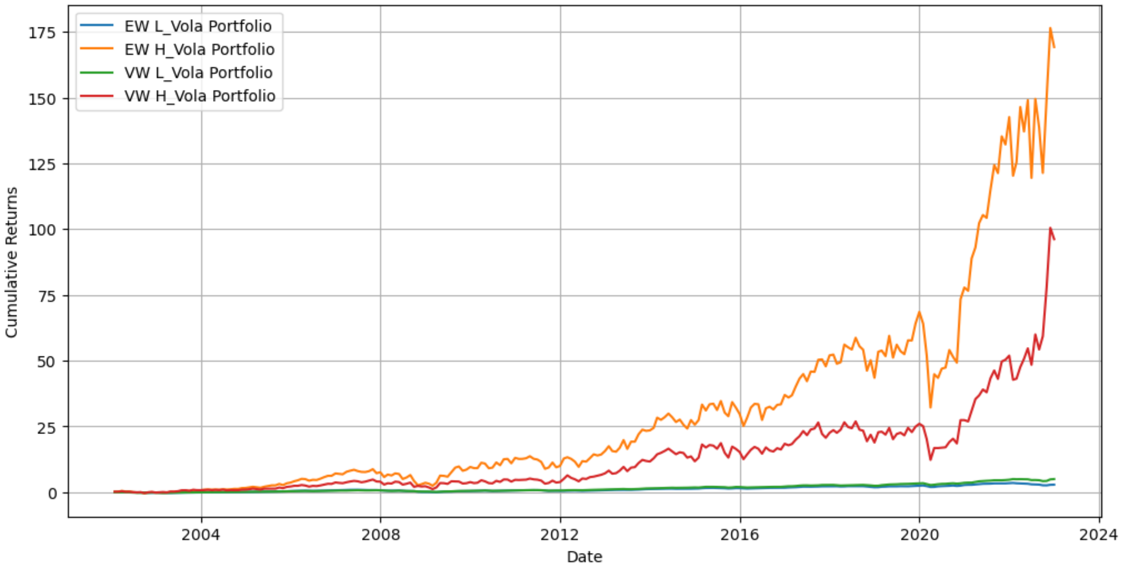
Graph 9: Cumulative Returns of all Portfolios in the Full-Sample period



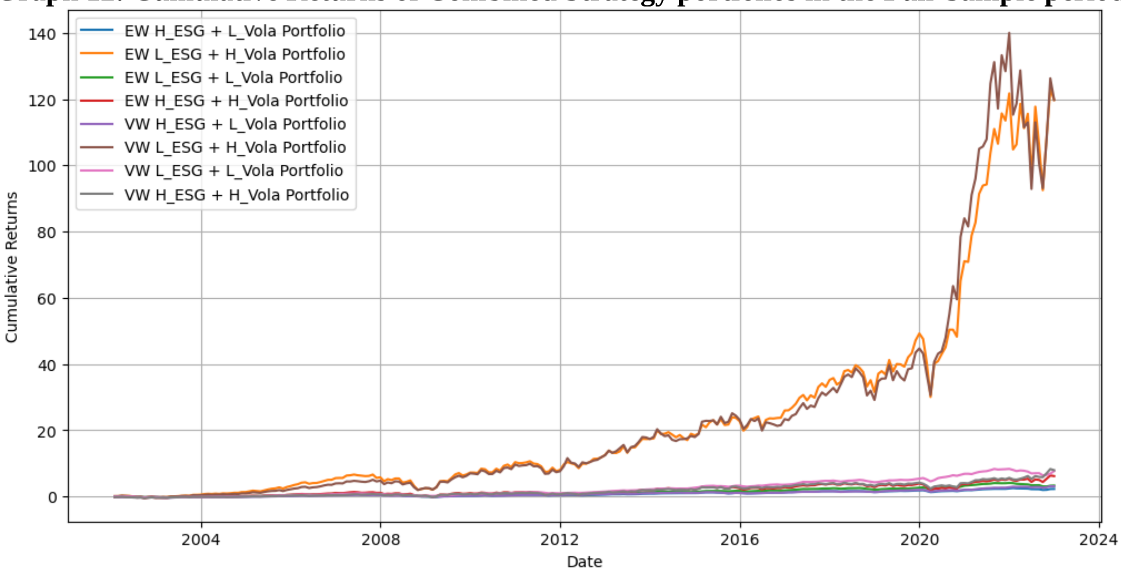
Graph 10: Cumulative Returns of ESG only portfolios in the Full-Sample period



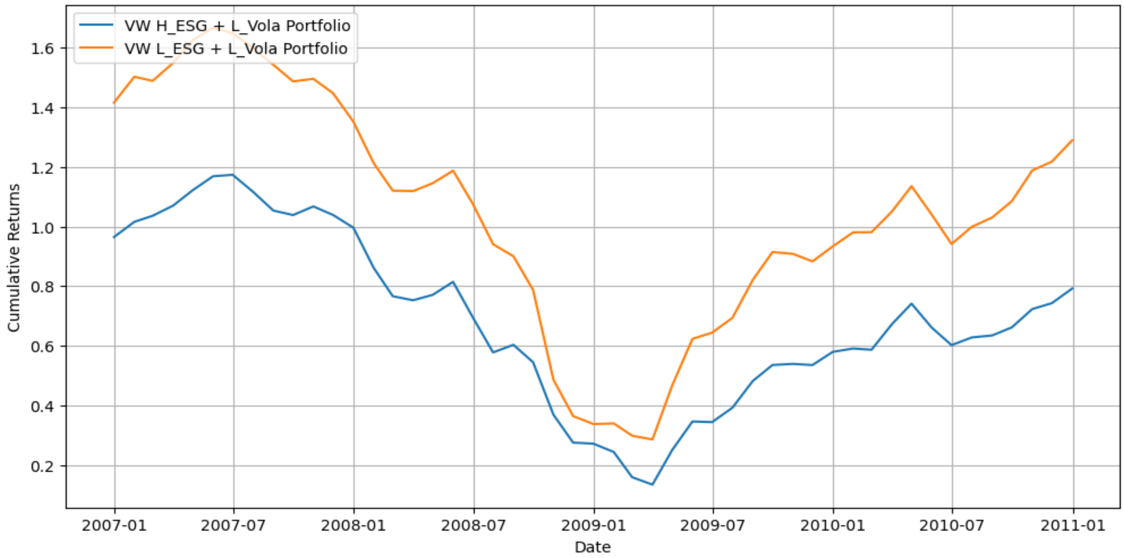
Graph 11: Cumulative Returns of Volatility only portfolios in the Full-Sample period



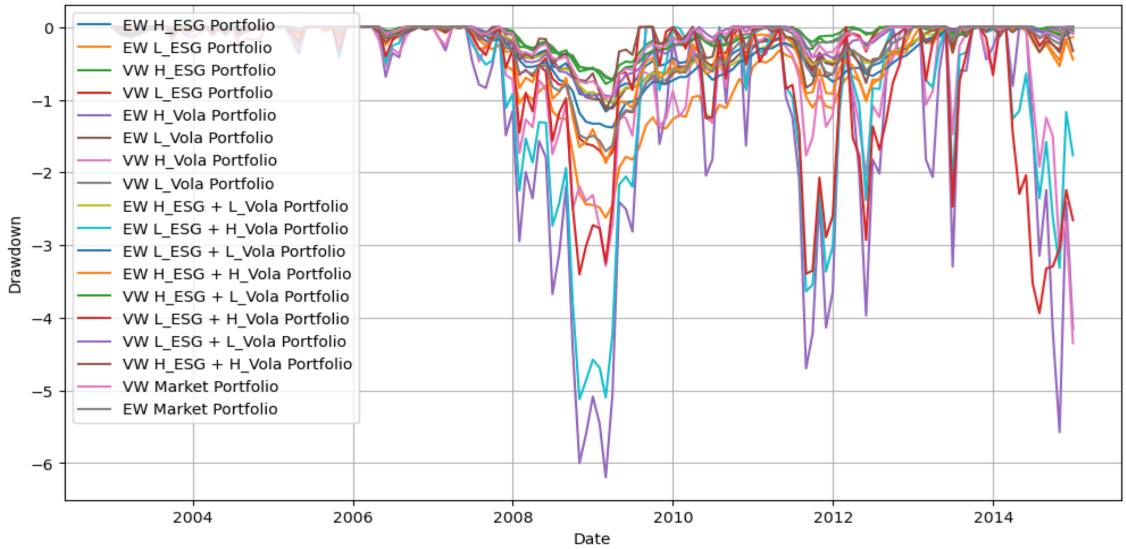
Graph 12: Cumulative Returns of Combined Strategy portfolios in the Full-Sample period



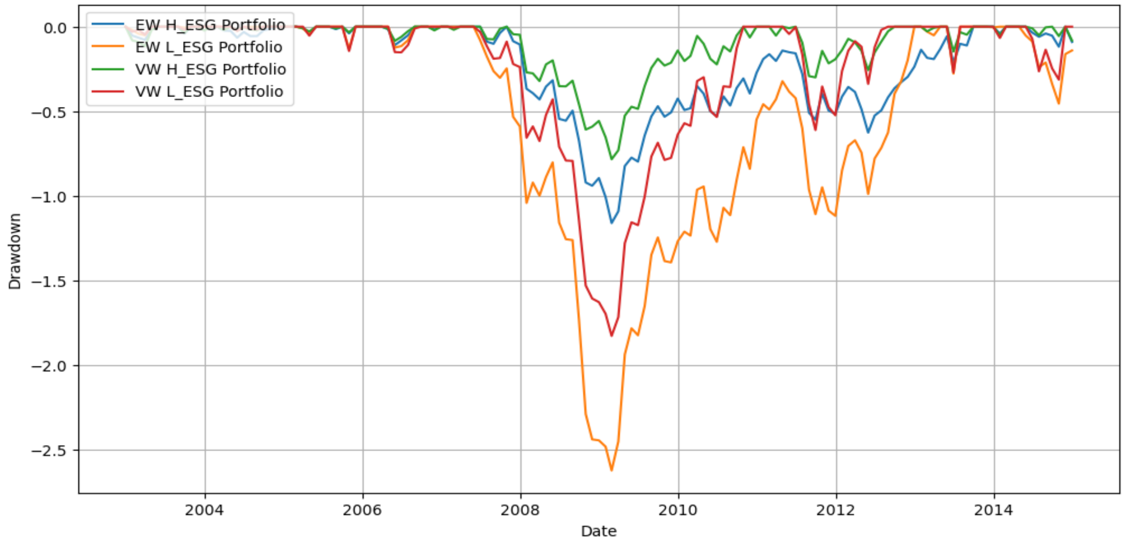
Graph 13: Cumulative Returns of portfolios during 2008 financial crises



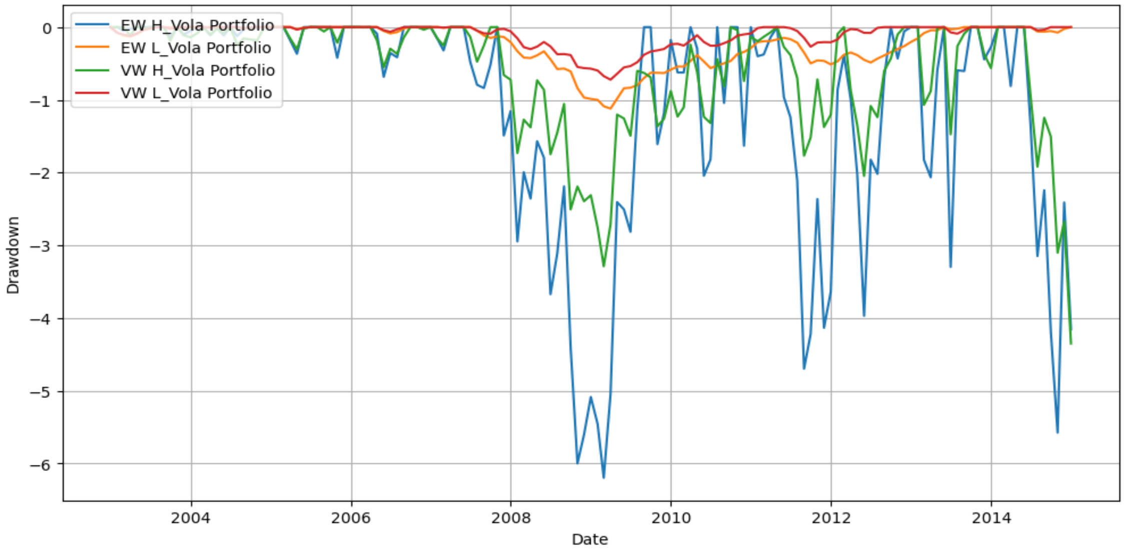
Graph 14: Drawdown of all Portfolios in the In-Sample period



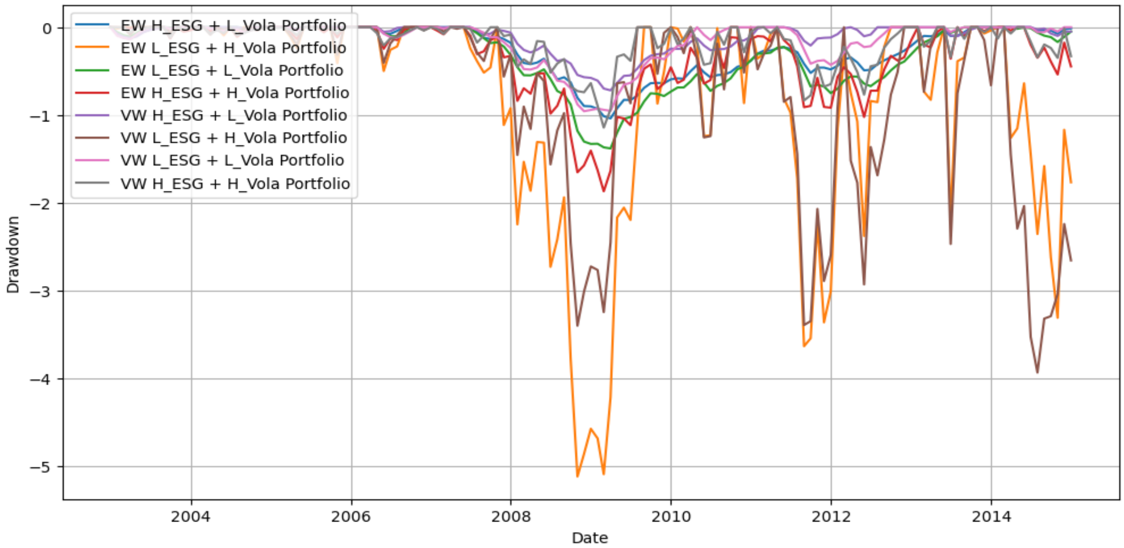
Graph 15: Drawdown of ESG only portfolios in the In-Sample period



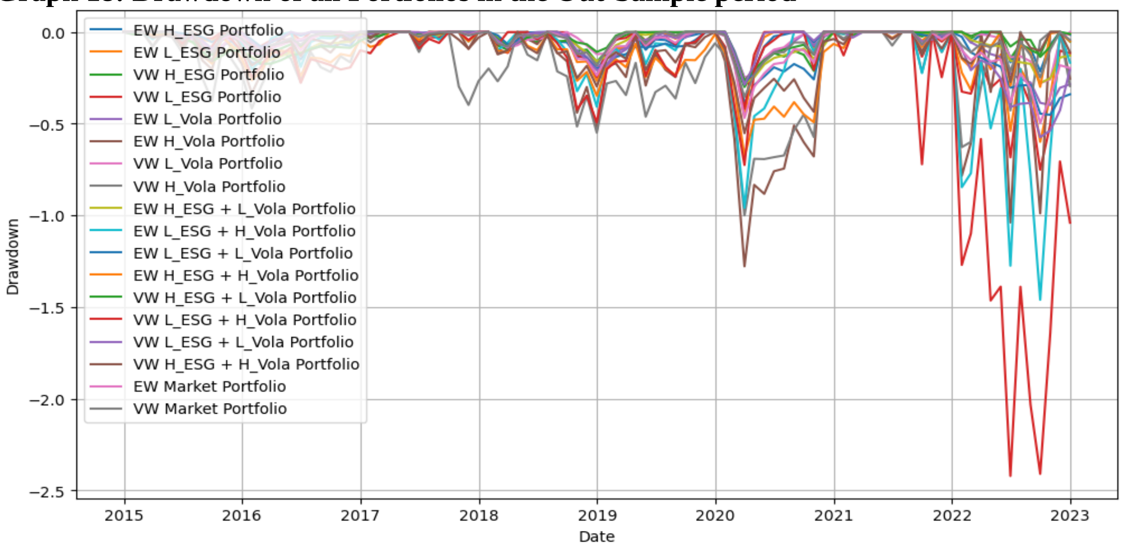
Graph 16: Drawdown of Volatility only portfolios in the In-Sample period



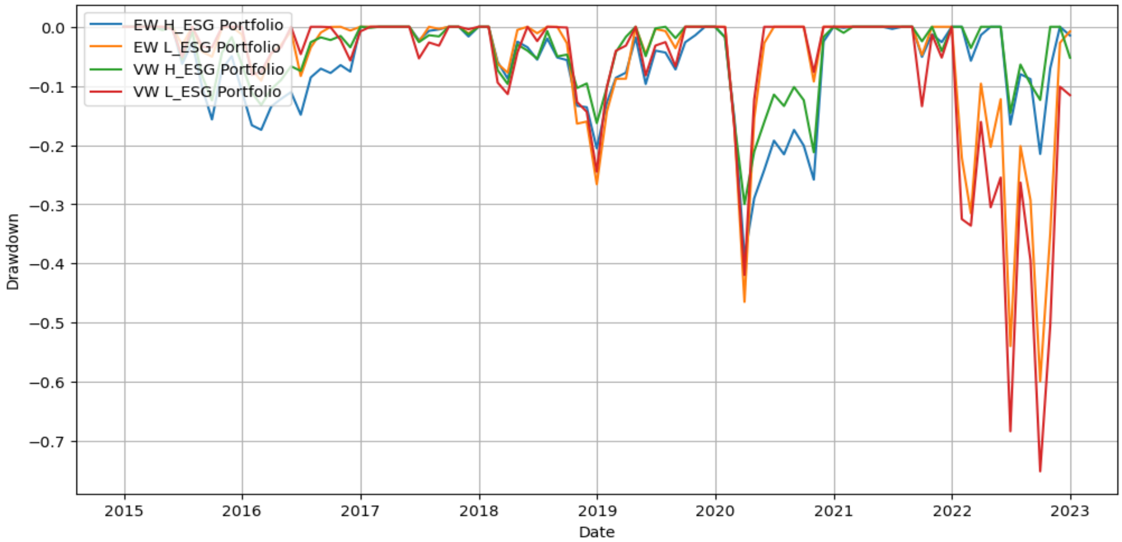
Graph 17: Drawdown of Combined Strategy portfolios in the In-Sample period



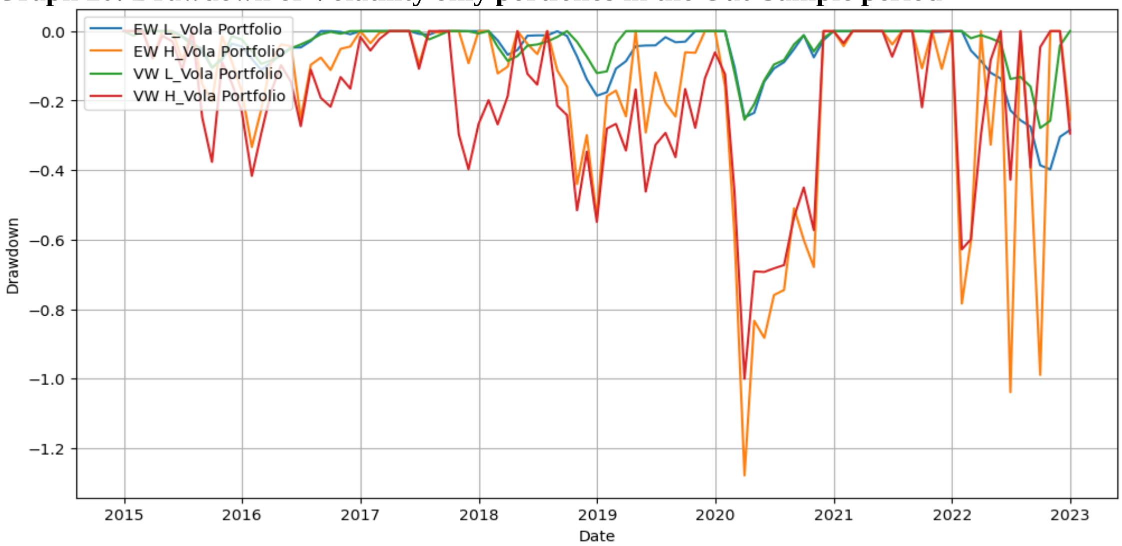
Graph 18: Drawdown of all Portfolios in the Out-Sample period



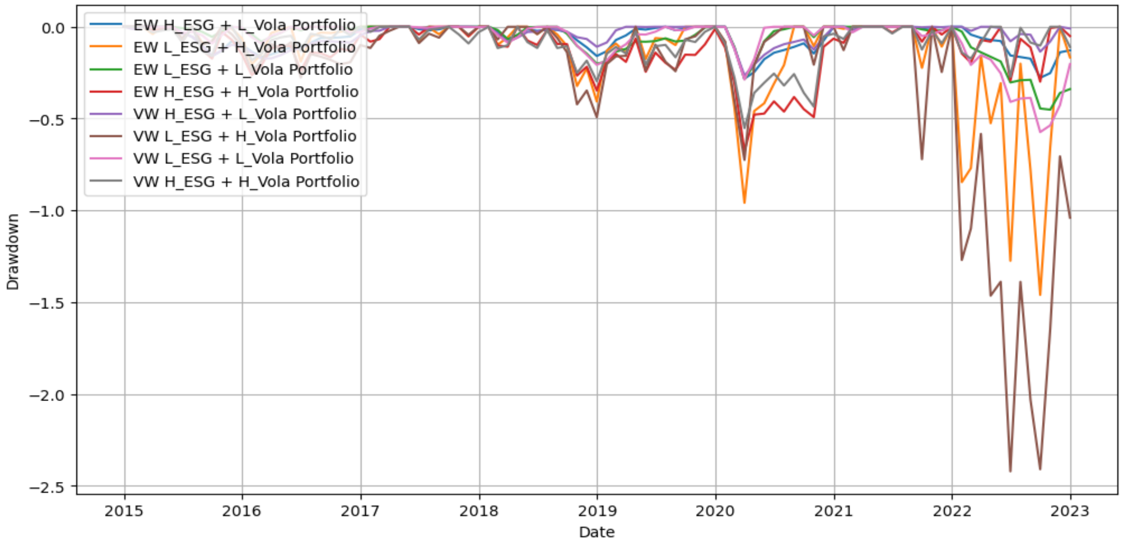
Graph 19: Drawdown of ESG only portfolios in the Out-Sample period



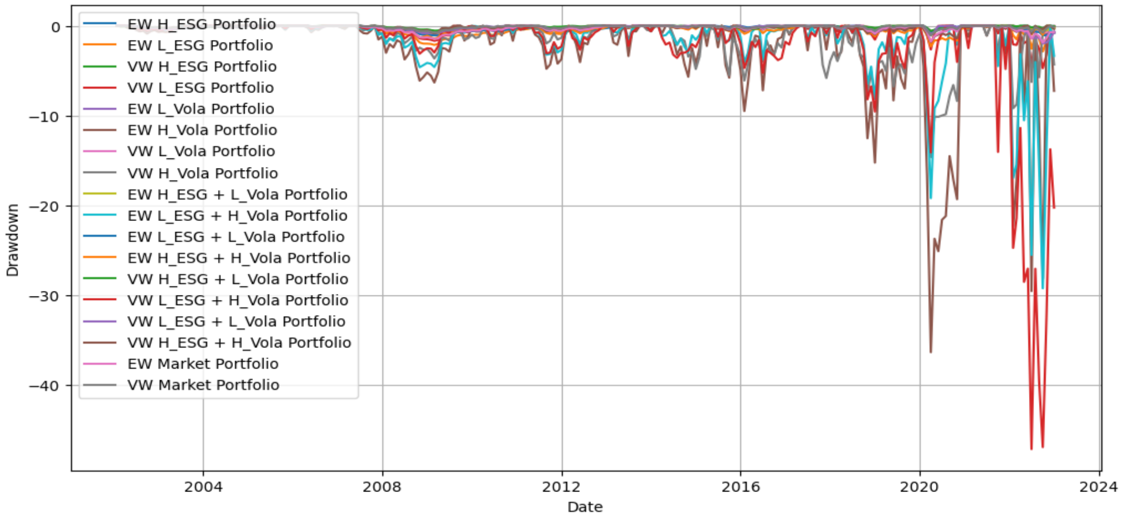
Graph 20: Drawdown of Volatility only portfolios in the Out-Sample period



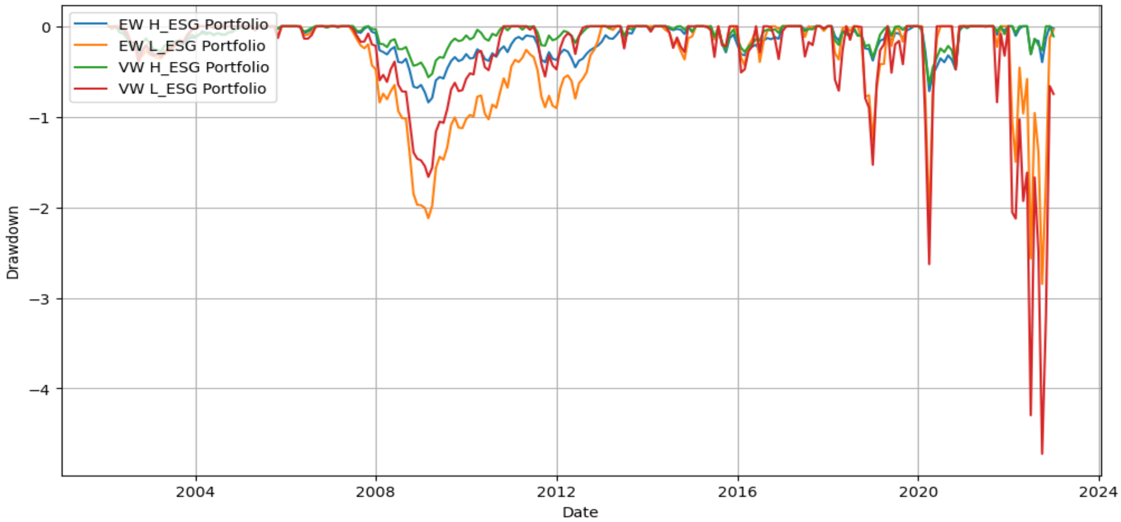
Graph 21: Drawdown of Combined Strategy portfolios in the Out-Sample period



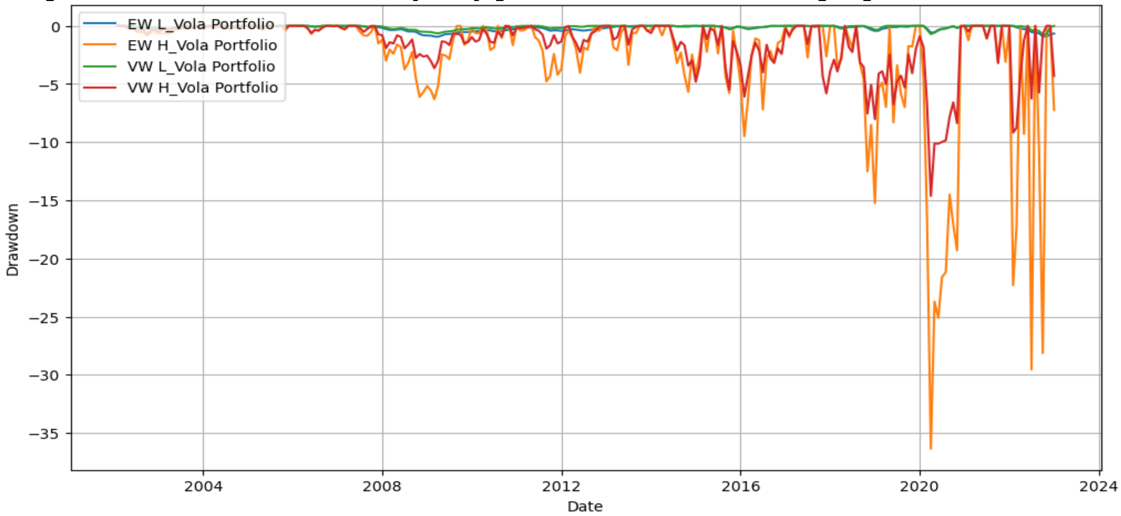
Graph 22: Drawdown of all Portfolios in the Full-Sample period



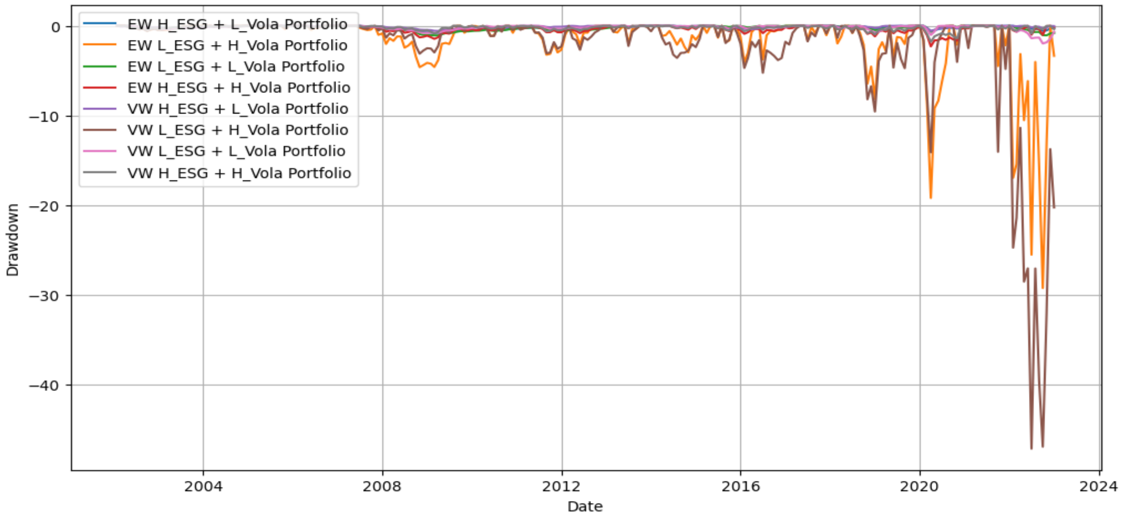
Graph 23: Drawdown of ESG only portfolios in the Full-Sample period



Graph 24: Drawdown of Volatility only portfolios in the Full-Sample period



Graph 25: Drawdown of Combined Strategy portfolios in the Full-Sample period



Group Part

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

ANALYSIS OF QUANTITATIVE INVESTMENTS STRATEGIES

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Group Part

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.

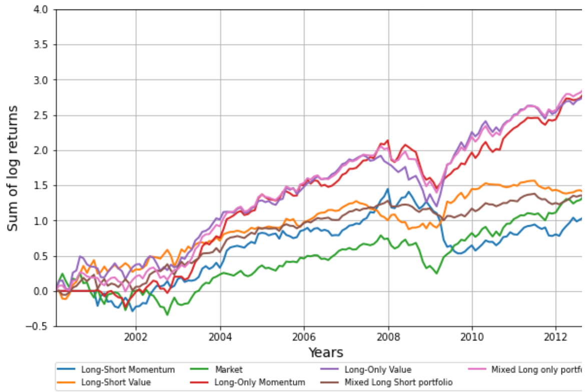

Figure 2: Cumulative Returns of the portfolios In-Sample

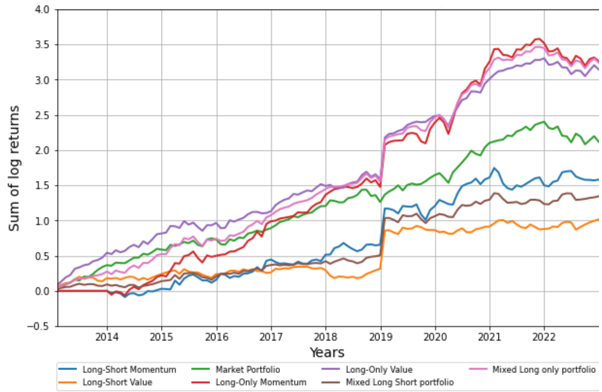

Figure 3: Cumulative Returns of the portfolios Out-of-Sample

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.

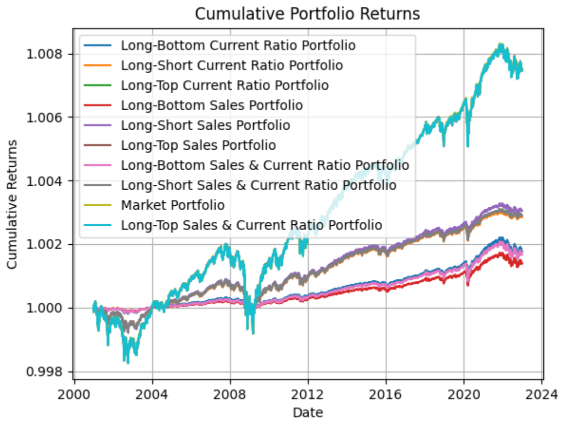

Figure 42: Portfolios' Cumulative Returns

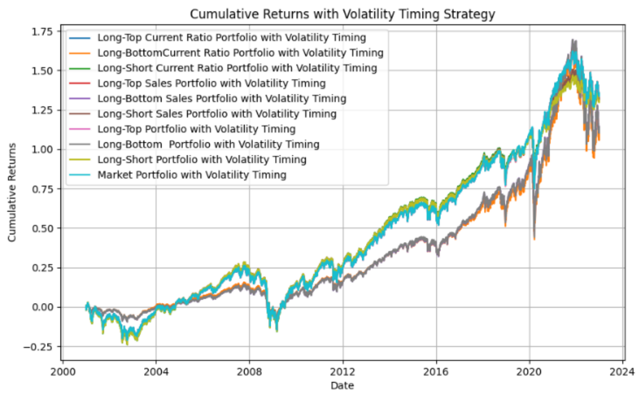

Figure 53: Portfolios' Cumulative Returns with a Volatility Timing Strategy

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.

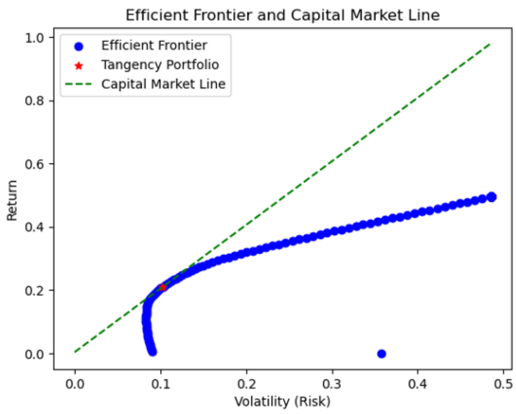

Figure 64: Efficient Frontier and Capital Market line

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.

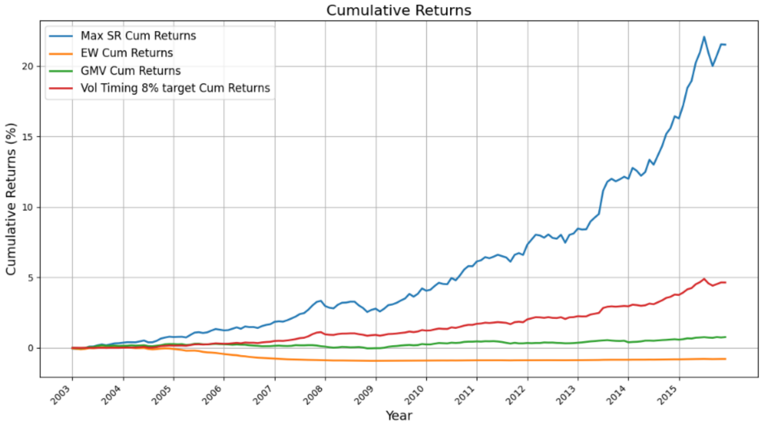

Figure 75: In-Sample Portfolios' Cumulative Returns

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.

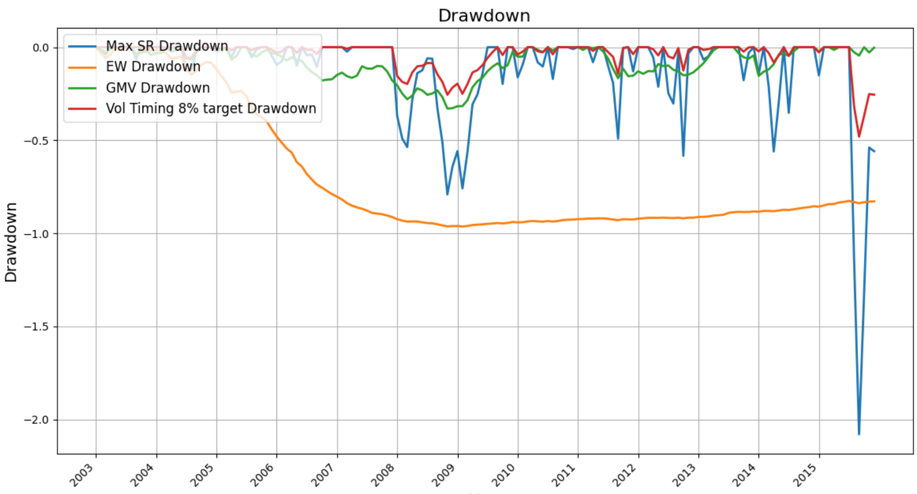

Figure 86: In-Sample Portfolios' Drawdowns

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 graphical representations of these portfolios' cumulative returns and drawdowns are shown in the appendix.

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.

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.

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.

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.

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 18: Out-Of-Sample Portfolios' Performance Indicators Results

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 19: Out-Of-Sample Portfolios' CAPM Results

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

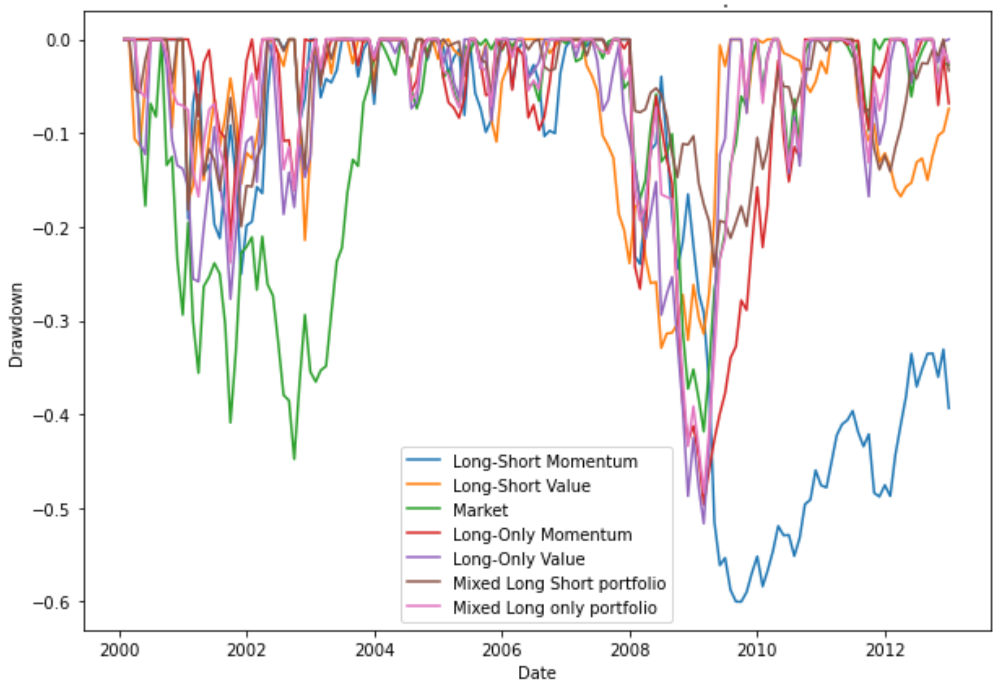

Exhibit 1: Maximum Drawdown of the Portfolios In-Sample

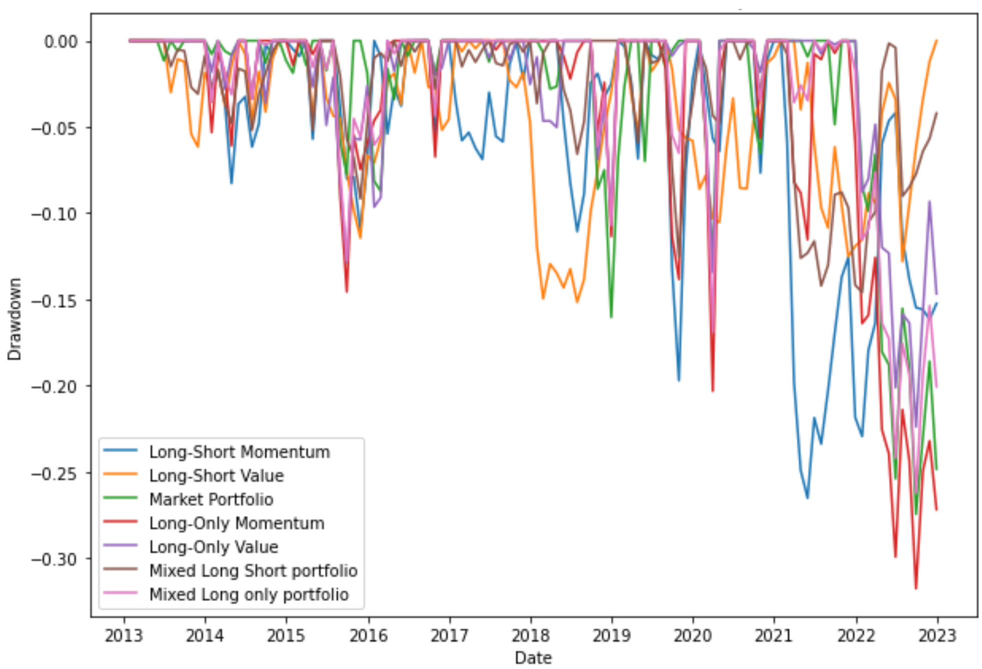

Exhibit 2: Maximum Drawdown of Portfolios Out-of-Sample

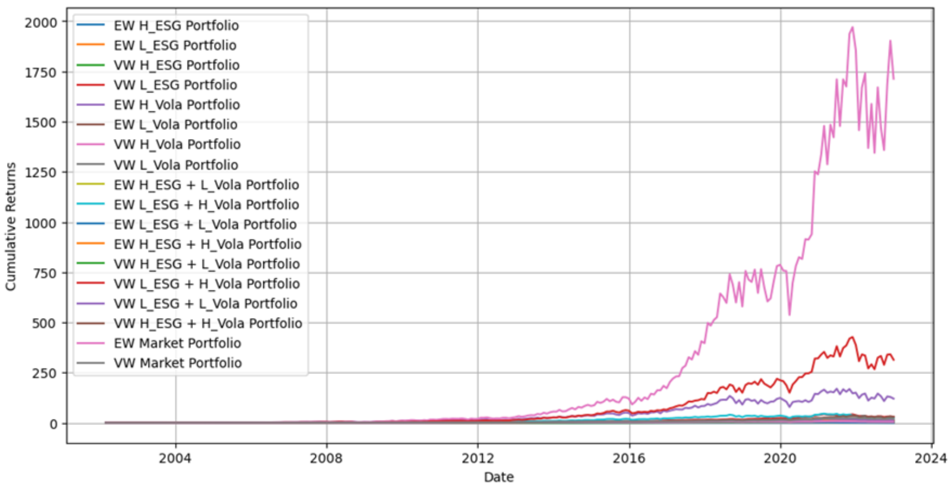

Exhibit 3: Cumulative Returns of all Portfolios in the In-Sample period

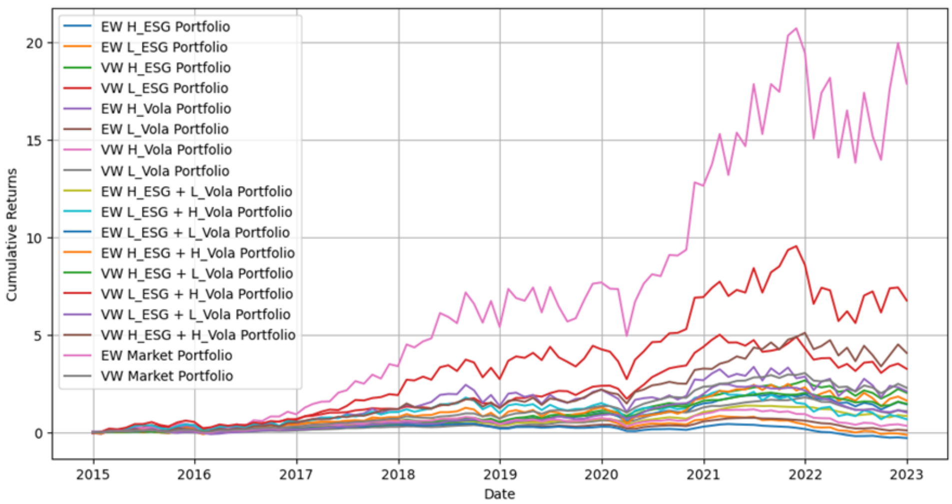

Exhibit 4: Cumulative Returns of all portfolios out-of-sample

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

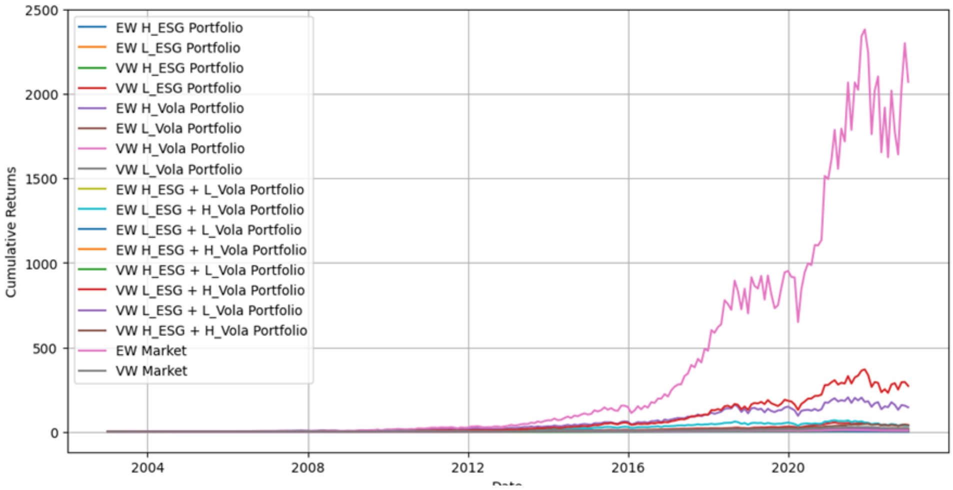

Exhibit 6: Cumulative Returns of all Portfolios in the Full-Sample period

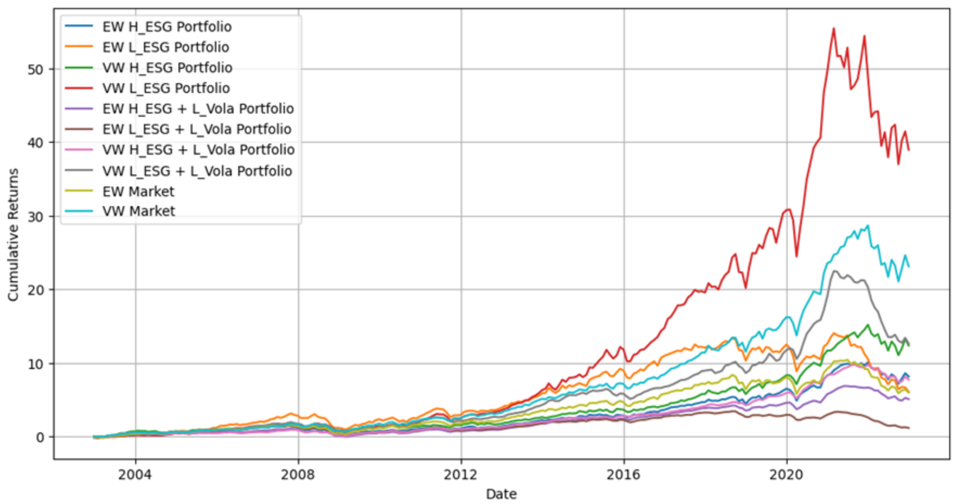

Exhibit 72: Cumulative Returns of the most relevant portfolios in the Full-Sample period

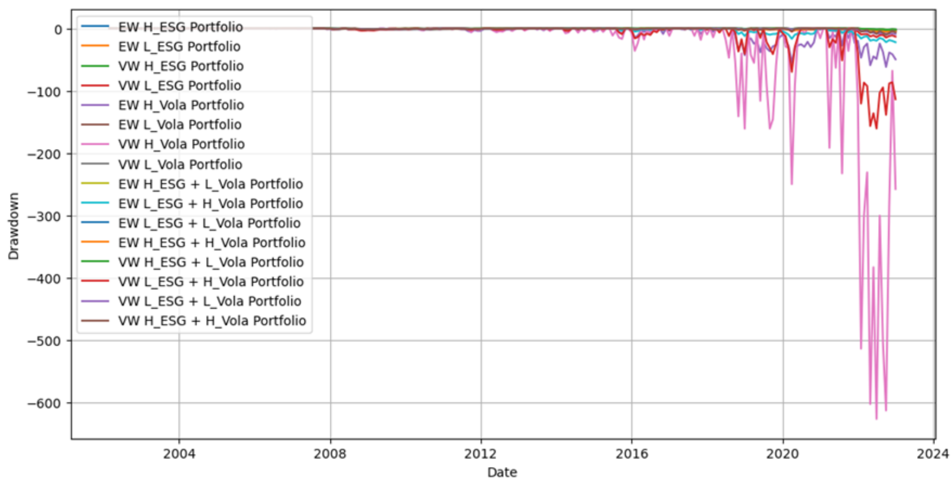

Exhibit 8: Drawdowns of all Portfolios in the In-Sample period

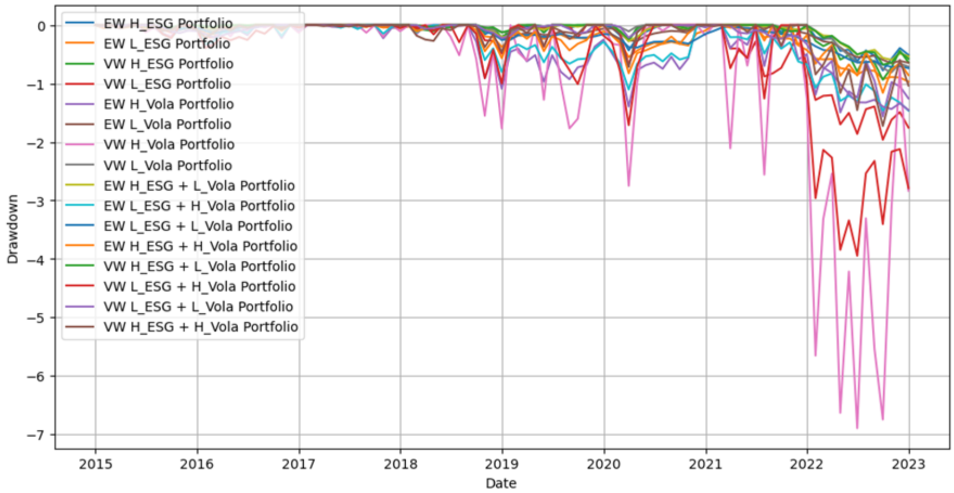

Exhibit 9: Drawdowns of all Portfolios in the Out-Sample period

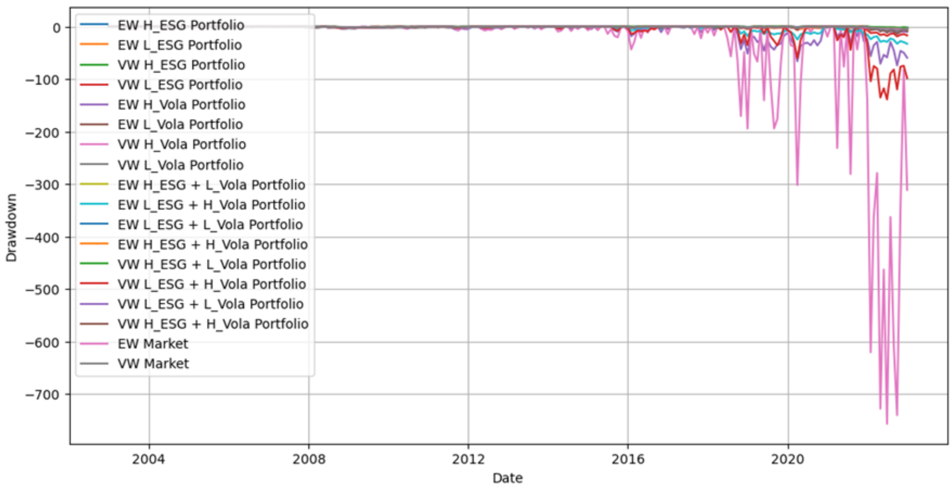

Exhibit 10: Drawdowns of all Portfolios in the Full-Sample period