# Work Project

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**International Master's in Finance**

Exploring Abnormal Returns of ESG Investments During the Covid-19 Crisis and the Russia-Ukraine War

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# Abstract

This Work Project examines the performance of ESG investments during the Covid-19 crisis and the Russia-Ukraine conflict. To evaluate their performance during these two periods, the work project considers three distinct portfolios constructed in line with the sustainability literature, drawing from companies listed in the Russell 3000 Index. The study spans from February 2016 to February 2024. While certain types of ESG investments yield abnormal returns throughout the entire duration, their significance diminishes when specifically scrutinizing the crisis periods, failing to reach statistical significance. To ensure robustness of the results, the work includes a multicollinearity test of the factors implied.

## Key words

Jensen's Alpha, Info Sharpe Ratio, Russell 3000, OLS, CAPM, FF3FM, FF5FM, Value Inflation Factor, Long Best in Class, Long Short, Long Worst in Class

# 1. Introduction

Over the last decade, the world has confronted two major crises: Covid-19, which significantly affected financial markets throughout 2020 and had enduring economic repercussions, and the ongoing Russia-Ukraine war, which commenced in February 2022 and persists to the present day.

The Covid-19 crisis impacted financial markets through the implementation of impressive countermeasures to limit the virus's spread, the enactment of fiscal recovery measures to mitigate its economic impact, and a reduction of interest rates to near zero to alleviate the strain on the banking system. Two years after the pandemic outbreak, the Russia-Ukraine conflict began generating geopolitical uncertainty, escalating risks, high volatility in energy markets and commodity prices, decreased investor confidence, and significant humanitarian costs to maintain safety in the conflict zones.

Both crises induced considerable market uncertainty, resulting in substantial losses across various sectors such as the stock market and the credit market. Despite enduring a recessionary phase, distinct industries within the S&P 500 showcased diverging performances during these crises. For instance, in 2020 alone, the Consumer Discretionary sector and the Energy sector of the S&P 500, identified as the best and worst performing industries in the index respectively, exhibited a disparity of over 70% in cumulative returns. Similarly, in 2022, the Energy sector and the Communication Services sector of the S&P 500, again identified as the best and worst performing industries, displayed a difference of over 90% in cumulative returns.

Given the significant sectoral discrepancies in the U.S. market, this study questions whether such differences are also observed in the context of ESG investments, and if so, what their magnitude is. Specifically, the study aims to analyze the performance and returns structure of ESG investments both during normal economic cycles and during periods of distress. To delve into this main topic, the study seeks to answer the following questions:

- *Did ESG ratings in US companies produce abnormal returns since 2016?*
- *How did ESG investments perform during stressed periods?*
- *Did ESG investments produce abnormal returns during crisis periods?*

The approach utilized in this study involves investigating the performance of ESG investments by constructing three different portfolios for each period under analysis. Performance will be measured using well-known metrics such as Annual Average Returns, Info Sharpe Ratio, Skewness, Kurtosis, and Maximum Drawdown. Once an understanding of each strategy's performance is obtained, the study will focus on understanding the drivers of the returns of each strategy using OLS estimator coupled with common return factors predictors suggested by the financial literature, namely the Capital Asset Pricing Model (CAPM), the Fama-French Three Factor Model (FF3FM), and the Fama-French Five Factor Model (FF5FM).

The outline of the Work Project is structured as follows:

Chapter 2 reviews research on the relationship between ESG scores and investment performance, as well as the effects of ESG scores on companies' financial performance. Chapter 3 focuses on the data collection process, the methodology applied for analysis, and the research perspective. Chapter 4 describes the results obtained from the complete analysis and methods for interpreting them. Chapter 5 presents the conclusions of this work, addressing the initial questions, and describes the limitations of the study.

# 2. Literature Review

## 2.1. ESG Introduction

Under a broad perspective Environmental, Social, and Governance (ESG) refers to a framework that measures the sustainable and ethical behavior of a business. The ESG factors ensure that a business is socially responsible in the best interest of shareholders and investors. Even though there is no definitive classification of these factors, and often factors can belong to more than one category, usually Environmental factors pertain to the quality of functioning of the natural environment and of natural systems. Social factors are related to the rights, well-being and interests of people and communities. Lastly, Governance factors pertain to the system of policies and regulations that are at the top of a community or entity. Overall, ESG factors may have a positive or negative impact on the performance of an entity. They can serve as a valuable resource by promoting healthy relationships with stakeholders and facilitating stable long-term growth. However, they can also act as a risk factor by constraining the entity from solely pursuing financial interests.

On a related note, ESG investing seeks to integrate traditional investment practices with considerations of governance, social impact, and ethical concerns. Essentially, ESG investing involves striving for competitive returns from assets while simultaneously promoting long-term value creation, environmental sustainability, and responsible corporate governance. Within the realm of ESG investing, the Principles for Responsible Investment (PRI), an investor-led initiative in collaboration with the United Nations, advocate for the incorporation of ESG factors into investment practices. They provide a range of actionable strategies for integrating ESG issues into investment decision-making.

There are several works in the financial literature that attempted to analyze ESG principles, ways to incorporate them in a corporate environment, and what is their impact on investment returns. Kempf and Osthoff (2007) studies the effect of socially responsible investinvesting (SRI) on portfolio performance using positive and negative screening for the period 1992-2004. The paper finds that applying the best in class approach, buying stocks with high ratings yields substantial abnormal returns up to 8.7% annually. Furthermore, the paper finds that the abnormal returns remain statistically significant and greater than 0 even after accounting for transaction costs.

Ma, N. (2023) in its study on integration of ESG factors in portfolio management attempts to analyze the relationship between ESG ratings and company performance, emphasizing how ESG factors impact cost of capital, employee satisfaction, and operational results. The research finds that companies with strong ESG performance often achieve better operational results and lower capital cost. Furthermore, the study concludes that ESG principles are becoming deeply integrated in the investment landscape, and that ESG performance is a crucial indicator of a company's commitment to resposnible business operations, which, in turn, impact the financial performance. Lastly, Servaes and Tamayo (2017) studies the U.S. stock market during the 2008-2009 financial crisis focusing on companies with high social capital, measured in terms of Corporate Social Reesponsibility (CSR) score. The research concludes that high-CSR firms expereince higher profitability, growth and sales compared to low-CSR firms. Additionally, the study evidences that firms with high CSR had stock returns 4-7 percentage points higher than firms with low CSR scores.

## 2.2. Capital Asset Pricing Model (CAPM)

The CAPM is a financial model developed in the late 1960s to calculate the expected rate of return on an investment. CAPM can calculate the expected return on an investment known the expected return on a rusk-free interest asset ($r_f$), or the minimum return an individual can expect for any investment, i.e. the expected return of the market ($r_m$), which is the rate of return that is observed by the market as a whole, and the relationship of the price movement of the investment with the market ($\beta$). In this work project, the market return considered is that of the S&P 500 index, while the risk-free rate is assumed to be the yield of a 10-year U.S. Treasury bond.Treasury Bond at each point in time. The relation of all variables in the CAPM is described in *Equation* (1).

$$r = r_f + \beta(r_m - r_f) \qquad (1)$$

## 2.3. Fama-French Three-Factor Model (FF3FM)

Subsequently, the financial literature realized the limitations of a single factor model, like the CAPM, and the importance of adding other factors besides the market factor in estimating expected returns. In 1993 Eugene Fama and Kenneth French decided to introduce the FF3FM, which supplemented the market factor with two firm-characteristic -size factor (SMB) and value factor (HML) - to enhance return predictability. Fama-French's rationale came from their observation that value and small cap stocks consistently outperformed the market, formulating a relation described in *Equation (2).*

$$r - r_f = \alpha + \beta_m\left(r_m - r_f\right) + \beta_{SMB}SMB + \beta_{HML}HML \qquad (2)$$

Where:

- $r$ = return of the investment
- $r_f$ = risk-free rate
- $r_m$ = return of the market
- $\alpha$ = Jensen's alpha
- $SMB$ = Small Minus Big
- $HML$ = High Minus Low
- $\beta_m$ , $\beta_{SMB}$ , $\beta_{HML}$ = coefficients of the three factors

SMB valuations take into account size, including the fact that smaller stocks will outperform larger stocks and the difference in returns between smaller stocks and larger stocks. HML values show the performance of high-to-market stocks (value) relative to low-to-market stocks (growth) and are calculated as the difference between the return on the value portfolio and the return on the growth portfolio.

## 2.4. Fama-French Five Factor Model (FF5FM)

Fama and French acknowledged that the Fama-French Three Factor Model (FF3FM) did not adequately explain the variability in average returns needed to forecast expected returns. They attributed this to quality factors, specifically profitability (RMW) and investment (CMA). Under their thesis profitability refers to the observation that stocks with a high operating profitability perform better than stocks with low operating profitability, and stocks with low level of investment (conservative) tend to outperform stocks with high level of investment (aggressive). Therefore, they came up with a relation of two additional factors using *Equation (3)*.

$$r - r_f = \alpha + \beta_m(r_m - r_f) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA \quad (3)$$

Where:

- $RMW$ = Robust Minus Weak
- $CMA$ = Conservative Minus Aggressive
- $\beta_{RMW}$ , $\beta_{CMA}$ = coefficients of the two additional factors

While the RMW value is calculated as the difference between the returns of companies with high operating profits and the returns of companies with lowoperating profits, CMA includes the returns of companies with low operating profits. Operating profitability and return on a portfolio of companies with low differences in investment activity.

## 2.5. Jensen's Alpha

In 1968, Michael C. Jensen introduced a measure called alpha, serving as a gauge of risk-adjusted return useful for determining the extent to which observed stock returns deviate from the returns predicted by the CAPM. In other words, alpha represents the portion of an investment's return that is not correlated with the market return. According to Jensen, this deviation from predicted returns, also known as "abnormal returns," could be used as a method for measuring a fund manager's performance against a benchmark. From this moment onwards in the Work Project, if the term “alpha” is used it refers to Jensen’s Alpha.

# 3. Methodology

## 3.1. Data Collection

The data was collected from the Bloomberg terminals for both ESG scores and stock market data using the Equity Screening (EQS) function, to which several filters were applied. To align with the objective of the work project, only companies included in the Russell 3000 index were taken into account. Subsequently, the sample was narrowed down to only those companies that reported an ESG score. Additionally, inactive companies were also included in the analysis to avoid survivorship bias. Once all the filters were applied, the ESG scores were collected according to the monthly BESG ESG SCORE, which provides the Bloomberg score evaluating the company's aggregated Environmental, Social, and Governance (ESG) performance. The score is based on Bloomberg's view of ESG financial materiality. The score is a weighted generalized mean (power mean) of Pillar Scores, where the weights are determined by the pillar priority ranking. Values range from 0 to 10, with 10 considered the best. In addition to the ESG score, the daily stock prices of all the filtered companies were downloaded to obtain the daily returns of the individual stocks, which were then used to compute the returns of the constructed portfolios. Finally, the sample was divided according to the two periods under analysis. The first sample consists of all those companies within the larger sample that reported an ESG score as of January 2018, excluding "new joiners" to ensure that an ESG practice has had sufficient time to be implemented and correctly evaluated in the score. After applying this additional filter, the sample was reduced to 1.213 companies. The second sample comprises all those companies within the larger sample that reported an ESG score as of January 2020, similarly avoiding the "new joiners" bias. After applying this filter, the sample was reduced to 1.091 companies.

## 3.2. Portfolios Formation

The portfolios were constructed following the most common strategies applied in ESG investing, namely positive screening, negative screening, and a combination of both. The analysis considered three different portfolios for each analysis period. All portfolios were built with monthly rebalancing, as the ESG scores were downloaded monthly, taking the daily return of the underlying stocks, and all the portfolios considered equal weighting. The three portfolios for each period were:

- Long Best in Class (LB)→ Investing in ESG entails using a positive screening criterion, which involves selecting the top 35 highest-scoring companies for a given month. Supported by financial literature, there are diversification benefits in a portfolio when investing in no more than 35-40 different stocks.
- Long Short (LS)→ Invests in ESG following both positive screening and negative screening criterion, which involved investing long in the top 20 highest scoring companies and investing short in the 20 worst scoring companies in each month.
- Long Worst in Class (LW)→ Follows the opposite criterion compared to the other two portfolios and is constructed to test the profitability of ESG investing. The portfolio invests in the 35 worst scoring companies each month.

## 3.3. Return and Performance Calculations

The returns computed for each of the three portfolios for all the periods follow the same logic. Firstly, for simplicity reasons, the natural logarithm of the returns was considered due to its additivity property, which simplifies the computation of the annual average return ($r_{p,annual}$) This can be achieved by applying the following formula in Excel: =+EXP(AVERAGE(Daily Returns)*252)-1, as there are typically 252 trading days in a year. Moreover, given that all the portfolios assume equal weighting of the underlying stocks, the daily returns of each portfolio are computed as a simple average of the returns of all the underlying stocks. However, since each portfolio rebalances according to changes in ESG score, rebalancing occurs monthly, meaning that each month the portfolios invest for 30 days in the same underlying companies. Lastly, since one of the three portfolios invests short in stocks, in that case the opposite of the daily return of the stocks was considered. Similarly, the annual standard deviation ($\sigma_{p,annual}$) of each portfolio was computed using the following formula: =+STDEV((Daily Returns)*SQRT(252)). Once Annual Average Return ($r_{p,annual}$) and Annual Standard Deviation ($\sigma_{p,annual}$) were computed, the main performance metric used to evaluate risk-adjusted performance of the portfolios was the Info Sharpe Ratio. Differently, to the Sharpe Ratio, the Info Sharpe Ratio (ISR) does not exclude the risk-free rate in the numerator. Therefore, it was computed using *Equation (4)*.

$$ISR = \frac{r_{p,annual}}{\sigma_{p,annual}} \qquad (4)$$

Aside from the risk-adjusted return an investor is interested in knowing the downside risk of the portfolio. This is measured through the Maximum Drawdown (MDD) which measures the maximum observed loss from a peak to a trough of a portfolio, before a new peak is attained, as shown in *Equation (5)*.

$$MDD = \frac{Through\ Value - Peak\ Value}{Peak\ Value} \qquad (5)$$

## 3.4. Empirical Models

In order to study the return composition of ESG investments and the quality of the results obtained, the Work Project considers the use of Ordinary Least Squares (OLS) regressions and Variance Inflation Factor (VIF) multicollinearity tests. OLS serves to describe the relationship between one or more independent quantitative variables and dependent variables. It is used to estimate the coefficients of independent variables in a linear regression. In this Work Project, all OLS regressions are computed with the Data Analysis tool pack available in Excel. The VIF analysis serves to measure the multicollinearity of independent variables in a regression analysis. Multicollinearity occurs whenever there is a strong correlation between multiple independent variables. Indeed, multicollinearity can adverse affect the results of a regression analysis by altering the sign and magnitude of the coefficients, thus making it difficult to determine the individual effects of each factor to the dependent variable.

# 4. Analysis

This part of the Work Project focuses on the analysis, performance comparison, and empirical results of the three ESG portfolios during the following time frame:

1. Performance analysis since 2016, named "Entire Period"
2. Performance analysis during the Covid-19 crisis, named "Covid-19"
3. Performance analysis during the Russia-Ukraine war, named "Russia-Ukraine War"
4. Performance analysis during the pre-Covid-19 pandemic, named "Pre-Covid-19 Period"

## 4.1. Performance comparison

### 4.1.1. Entire Period

The first period taken under analysis includes the period from February 2016 and April 2024. The results of the three portfolios in Exhibit 1Exhibit 1 together with those of the S&P500 Index. The cumulative return of the S&P 500 was used as a comparison instrument to use at hand the performance of a traditional investment instrument during that same period. As observed, the S&P 500 outperformed all other assets. Both the LS portfolio and the LB portfolio performed similarly, while the LW portfolio performed the worst. Notably, as reported in Table 1, the Long Short portfolio had the lowest risk in terms of Annual Standard Deviation and MDD. This was primarily accomplished because, regardless of the ESG score, all stocks incurred losses during the pandemic outbreak, as evidenced by the negative performance of the S&P 500 during that period. Having short positions helped alleviate the decline in returns for that period. Additionally, having half of the portfolio invested long and half invested short constributes to the stability of returns. During economic expansion, the portfolio sacrifices potential upside, but during crises such as the Covid-19 pandemic, it mitigates potential downside. Moreover, it can be noted that the LW portfolio initially performed similarly to the other portfolios throughout 2016 but then began to underperform. This could be attributed to the growing emphasis on incorporating ESG criteria into investment strategies starting in 2017. Lastly, under a risk-adjusted performance perspective, the S&P 500 showed the best Info Sharpe Ratio (ISR) 0,7.

### 4.1.2. Covid-19

Taking a closer look at the Covid-19 crisis period in Exhibit 2, which includes the entirety of 2020 and 2021, the LB portfolio and the LS portfolio exhibited similar cumulative performances.

However, despite achieving comparable total returns, the two portfolios demonstrated contrasting risk-adjusted performances, as highlighted in Table 2. Specifically, they reported varying levels of Annual Standard Deviation and MDD, leading to significantly different IRSs. Moreover, the inclusion of short positions in the LS portfolio effectively mitigated the crisis's early adverse impact. Finally, while risk metrics for the LW portfolio closely resemble those of the LB portfolio during the period, its negative returns render the entire strategy unattractive.

Some of the return's features for the period under analysis can also be interpreted from Exhibit 3. Indeed, although all three strategies exhibit negative skewness, the LS portfolio appears to be the least negatively skewed. This suggests that it experienced comparatively lower "tail" losses during the crisis outbreak. Moreover, the return's stability of the LS portfolio can also be observed by the low kurtosis (mesokurtosis), indicating that few returns were in the tail, of the distribution. Lastly, the higher leptokurtosis of the LB portfolio compared to that of the LW portfolio can be partially explained by the slightly higher level of (MDD).

#### 4.1.3. Russia-Ukraine War

The third period taken under analysis involves the entirety of 2022 and 2023. As Exhibit 4 shows the cumulative performance seems to be profitable only for the LS portfolio. Indeed, both the LB strategy and the LW strategy report negative average annual returns as Table 3 shows. The significantly positive results of the LS portfolio can be attributed primarily to the equally balanced long and short positions. The balance is evident when approximating by subtracting the average annual return of the LB portfolio (-9,66%) from that of the LW portfolio (-19,86%). However, it's important to note that this is just an approximation due to the LS strategy's daily investment in a varying number of companies. The approximation becomes clearer when comparing the realized Average Annual Return of the LS portfolio (10,89%) with the difference in returns of the other two portfolios (10,2%). The discrepancy between the two strategies stems from the reduced diversification. Investing long in 20 companies compared to 35 results in higher returns, and the same principle applies to the worst-scoring companies. Additionally, the negative performance of the LS portfolio aligns with the positively skewed and platykurtic nature of its return distribution. Indeed, a positively skewed curve is one such that experiences on average negative returns but few large returns in the fat tail. Instead, a platykurtic curve is one that has more concentration of returns around the mean and consequently less likelyhood of extreme returns . Therefore, the portfolio's tendency towards more frequent negative returns, coupled with its reduced likelihood of extreme fluctuations, contributes to its underperformance.

#### 4.1.4. Pre-Covid-19 Period

In the pre-Covid-19 period, spanning from February 2016 to December 2019, the LB portfolio reported the highest cumulative performance, as depicted in Exhibit 6. Notably, during non-crisis periods, the LS strategy did not perform as well as during crisis periods. This can be attributed to the less effective nature of short positions in mitigating upside returns compared to crisis scenarios. Furthermore, until the end of 2016, the LW strategy closely mirrored the performance of the Long Best in Class, indicating a market shift towards increasing demand towards ESG-focused investments. The LS strategy exhibited the lowest Annual Standard Deviation, as shown in Table 4, primarily driven by its two-sided exposure to the market. Moreover, in Exhibit 7, it is possible to observe that during normal market conditions, the return distribution of all three strategies tends to exhibit the typical negatively skewed shape and low levels of kurtosis.

## 4.2. Empirical Results

This section of the Work Project delves into the empirical findings derived from employing OLS regression analysis on the observed samples. The study will mirror the time periods outlined in the Performance Comparison section, but with a twist: only the top-performing strategies in terms of risk-adjusted returns (ISR) will undergo regression analysis for each period. During the "Entire Period," all three portfolios will be scrutinized to grasp their overall performance across a complete economic cycle. In the "Covid-19" period, the analysis will focus solely on the returns of the LB and the LS portfolios due to their positive Annual Average Return. Throughout the "Russia-Ukraine War" period, attention will shift exclusively to the returns of the LS portfolio, the sole portfolio reporting a positive annual average return during this period. Lastly, during the "Pre-Covid-19 Crisis," analysis will concentrate on the returns of the LB and the LS portfolios, again due to their positive annual average return.

The objective of this section is to understand the composition of the returns of each strategy analyzed in the previous section and discover if the strategies applied deliver abnormal returns and to what degree these are statistically significant. Indeed, conducting regressions on the returns of each strategy for each specific period enables us to comprehend the factors influencing returns and assess their relevance for the chosen sample. Furthermore, for each period, three empirical models are considered: the CAPM, FF3FM, and FF5FM. The rationale applied here is that conducting regressions for each model successively enables to grasp how additional factors can impact the quality of the results, either positively or negatively. This helps discern whether improvements are randomly driven or if they provide a meaningful explanation of the model. In all the empirical analyses, alpha aligns with the intercept of the regression and is derived by regressing the returns of a portfolio net of the risk-free rate with all the variables of a given model except the risk-free rate. Consequently, the intercept encapsulates the portion of returns not accounted for by the independent variables, which precisely represents abnormal return. Lastly, in each regression analysis, an independent variable is deemed statistically significant only if it falls within the 95% confidence level.

### 4.2.1. Entire Period

Regarding the LB portfolio, the results presented in Exhibit 8 using the CAPM show a promising R-Squared (0,82), which proves that the regression model predicts the outcome of observed data with precision. Additionally, it is noteworthy that the coefficient associated with the market minus the risk-free rate factor (Mkt-rf) of 0,96, which represents $\beta_m$, indicates that the portfolio's volatility is highly correlated with the market. Finally, the regression model confidently shows that the LB strategy is capable of generating a negative yearly alpha of -8,5%, which is statistically significant even at the 99% confidence level.

As for the LS strategy, the regression model yields a very low R-Squared (0,06). This can be partly attributed to the portfolio's two-sided long and short positions in the market. Indeed, the factors of the CAPM regression model seem unable to adequately explain the observed values. Furthermore, the p-value for the intercept of 0,46 indicates that the portion of results not predicted by the market is likely driven by pure randomness. Therefore, the results obtained are insufficient to provide an explanation, and further factors need to be considered using the FF3FM and the FF5FM. Finally, regarding the LW strategy, it can be observed that the R-Squared is lower than that of the LB strategy but still significantly higher than that of the LS strategy. Furthermore, the regression results indicate that this strategy possesses a statistically significant yearly alpha of -19,06%. Despite all factors being statistically significant, this finding is not entirely convincing on its own, as the intercept in the CAPM model appears to be very large and may include factors not captured by a single-factor model. Therefore, further analysis using the FF3FM and the FF5FM with additional factors will provide better explanations.

The findings of the regression analysis for the FF3FM can be found in Exhibit 9. As indicated by the LB regression, adding two variables to the model slightly improves its precision, resulting in an R-Squared of 0,85. Moreover, it is observable that both the SMB and the HML factors have positive coefficients and are statistically significant, suggesting that part of the returns are driven by smaller companies performing better than larger companies and value companies outperforming growth companies. Additionally, with the FF3FM, it can be observed that the value of alpha is reduced in absolute value. This indicates that the two additional factors helped capture part of the alpha observed in the CAPM model. Regarding the LS strategy, it is evident that incorporating two additional factors to the CAPM slightly enhanced the quality of the regression analysis. However, the analysis still exhibits a very low R-Squared value (0,08), suggesting that the model does not encompass all variables associated with the observations. In addition, the empirical results show a statistically insignificant alpha and HML factor, while the SMB and the Mkt-fr are statistically significant, with a negative coefficient for the SMB factor indicating that the returns of the strategy are driven by large-cap companies outperforming small-cap companies. Examining the LW strategy, it becomes evident that employing the FF3FM significantly enhances the quality of the empirical results. This improvement is driven by the inclusion of the two additional factors. Moreover, the absolute value of the annual alpha is reduced compared to the CAPM, meaning that part of the original returns are captured by the added factors. Lastly, taking a look at the FF5FM in Exhibit 10, it is possible to observe that with the addition of two further models, namely the CMA and the RMW, the quality of the empirical results of all strategies is improved. In particular, the LB strategy confirms a negative statistically significant yearly abnormal return of -8,42% and a positive coefficient on the two added factors, in line with what Fama and French predicted when developing the 5 Factor model. As for the LS portfolio, the improvement of the R-Squared to a value of 0,11 indicates that the model lacks variables to predict the observed outcomes. Furthermore, enhancing the model including 5 factors did not contribute to reducing the p-value on the intercept. Consequently, for the entire period, the LS strategy exhibits a positive yearly alpha of 0,83%, which is not statistically significant. Moreover, using FF5FM, the sign on the coefficient of the HML factor changed, evidence of the lack of robustness of the empirical results. Lastly, the LW portfolio confirms a statistically significant negative yearly alpha of -16,53%. Also, the inclusion of the two factors with negative coefficients suggests that returns in this strategy are influenced by aggressive companies outperforming conservative ones and low operating profitability companies outperforming high operating profitability ones.

#### 4.2.2. Covid-19

Exhibit 11 presents the results of the OLS regression of the CAPM on the LB and LS portfolios. As observed, the CAPM alone accounts for predicting the majority of the observations, with an R-squared of 0,85, and possesses a market beta $\beta_m$ slightly above 1, which is higher compared to that of the "Entire Period" using the CAPM. This is consistent with the principle of sample variability, according to which larger samples with more observations have less variability compared to smaller samples because they provide a more accurate representation of the population. Furthermore, the empirical results showcasted a negative yearly alpha of -11,13%, which is not statistically significant. On the other hand, the regression results for the LS portfolio exhibited low values of R-squared, driven by the two-sided exposure in the market. The LS strategy reports a positive yearly alpha of 6,41%, which, however, is not statistically significant.

The results of the FF3FM can be examined in Exhibit 12. As evident, enhancing the analysis by incorporating two additional factors improved the outcomes for both the LB and the LS portfolios, resulting in a higher R-Squared compared to the CAPM. Specifically, the coefficients for the three factors closely resemble those of the "Entire Period"; however, alpha continues to lack statistical significance. Regarding the LS portfolio, despite the enhanced quality of the results, alpha remains statistically insignificant, and the HML factor lacks statistical significance.

Lastly, as Exhibit 13 shows, the FF5FM results do not bring significant improvements to the FF3FM for both the LB portfolio and the LS portfolio. More specifically, although the R-squared improved for both strategies, the additional explained variance in the observations is insufficient to render the alpha of both strategies statistically significant. Additionally, this improvement causes the RMW factor to be statistically insignificant in the LB strategy, and the SMB, HML, and CMA factors of the LS strategy to be statistically insignificant. Thus, it is possible to conclude that for the Covid-19 period, there seem to be negative abnormal returns for the Long Best in Class portfolio and positive abnormal returns for the Long Short portfolio that are not statistically significant.

### 4.2.3. Russia-Ukraine War

Next, considering the Russia-Ukraine War period depicted in Exhibit 14 it is possible to observe that the regression results show a very low R Square of 0,01, with a positiv yearly alpha of 7,79% which is not statistically significant. Once again the low value of the R-Square can be motivated by the opposing nature of the positions taken in the market by the LS portfolio. However, $\beta_m$ apepars to be lower compared to the previous periods, which points to the fact that during the Russia-Ukraine War the returns of the LSportfolio were less correlated to the market compared to other periods. Moving to the results of the FF3FM available in Exhibit 15, it is possible to observe that the R-Square is improved (0,05), and the yearly alpha is positive (6,97%) but not statistically significant. Lastly, the signs on the coefficients appear to be consistent with those of all previous periods, indicating no structural change in the composition of the returns.

To conclude, the results for the FF5FM are presented in Exhibit 16. Once again the explanatory power of the model appears limited with an R Square of 0,08. Moreover, the inclusion of two additional factors caused the HML coefficient to change sign, rendering it statistically insignificant, and did not enhance the quality of the results regarding the intercept. Therefore, it is possible to conclude that during the Russia-Ukraine War period the LS portfolio reports negative alpha, but statistically insignificant at any confidence interval.

#### 4.2.4. Pre-Covid-19 Period

The empirical findings are displayed in Exhibit 17. The CAPM largely explains the observed returns of the LB portfolio, with an R-Squared of 0,77. The yearly abnormal return for the period analyzed is higher in value (-4,04%) compared to other periods but remains not statistically significant. Concerning the LS portfolio, the R-squared is notably low, consistent with other periods, along with the positive yearly alpha (0.74%), which lacks statistical significance.

Enhancing the model with two additional factors using the FF3FM improves the explanatory power of the results, yielding a higher R-Squared compared to the CAPM, as evident in Exhibit 18. Similar to other periods, the FF3FM coefficients for the LB portfolio are all positive and statistically significant, while the yearly alpha is negative (-3,75%) and not significant. However, for the LS portfolio, the results deviate from previous periods, with the coefficient on the HML factor negative, suggesting that part of the returns were driven by growth stocks outperforming value stocks. The alpha is positive and not statistically significant at any confidence interval.

Lastly, examining Exhibit 19, which presents results using the FF5FM, it is observed that the R-Squared is improved for both strategies compared to the previous models. Moreover, while for the LB strategy, both the intercept and the HML factor are not statistically significant, for the LS strategy, all factors except the intercept are statistically significant. Consequently, it can be concluded that in the Pre-Covid-19 Period, the LB  strategy reports a negative alpha, while the LS strategy reports a positive alpha; however, both lack statistical significance.

## 4.3. Multicollinearity

This part of the Work Project will be focused on understanding the interaction of the variables applied in the regression models for each period using the Value Inflation Factor (VIF) analysis, which measures the multicollinearity of variables. Given that the focus of this work is to understand the nature of ESG investments particularly during recessionary periods, the VIF will be conducted only for the Covid-19 period and the Russia-Ukraine War period. For quality purposes, the VIF will be computed on the factors in the Fama-French 5 Factor model, as being more explanatory of an asset's return in the financial literature. The analysis will be conducted by considering the single correlation of each factor, studying the correlation coefficient of each factor with the others. To understand the correlation the single factor with all the other factors combined, the analysis will include a VIF multicollinearity test. The test was conducted calculating the R-Squared resulted from regressing each factor against all other factors.

The VIF value is then computed using the formula in *Equation (6):*

$$VIF = \frac{1}{(1 - R^2)} \qquad (6)$$

For the purpose of this analysis, a value lower than 3 indicated low or no multicollinearity. A value higher than 3 for each factor was considered an indicator of moderate multicollinearity, while a value higher than 5 indicated strong multicollinearity.

### 4.3.1. Covid-19

As shown in Exhibit 20, for the Covid-19 crisis period, the factors that displayed moderate correlation were CMA and HML, with a correlation coefficient of 0,56. However, upon further analysis and calculation of the multiple correlation by gathering the variables' R-Squared and applying *Equation (6)*, it was shown that none of the variables demonstrated either moderate or strong multicollinearity. Thus, it was possible to conclude that there was no case of singularity among the variables in the FF5FM during the Covid-19 period.

### 4.3.2. Russia-Ukraine War

Focusing on the Russia-Ukraine War period, it was evident from Exhibit 21 that the linear correlation table already indicated correlations between CMA and Mkt-rf, as well as between CMA and HML factors. Therefore, upon conducting a multicollinearity test, it became apparent that, both CMA and HML demonstrated moderate values of multicollinearity, namely 3,26 and 3,08. This suggested that the coefficients obtained in the FF5FM regression for CMA and HML factors might not have been reliable when estimating the results, potentially influenced by correlations with other coefficients. To address this issue, a second VIF analysis was carried out using FF3FM to assess whether multicollinearity would have been alleviated by removing one of the "biased" factors in the 5-factor model. The results are presented in Exhibit 22. The hypothesis was confirmed both in the linear correlation analysis and the VIF analysis, as the HML factor, which originally exhibited moderate correlation, obtained a VIF value of 1,29.

# 5. Conclusions

The objective of this Work Project is to comprehend the performance and return dynamics of ESG investments across the complete economic cycle and during times of distress. To achieve this, portfolios comprising high ESG scoring companies, low ESG scoring companies, and a blend of the two are formed within the Russell 3000 index spanning from February 2016 to February 2024.

- *Did ESG ratings in US companies produce abnormal returns since 2016?*

The study reveals that both the Long Best in Class and Long Worst in class generated negative yearly abnormal returns in the Entire Period of analysis of -8,42% and -16,53% respectively using the FF5FM. At the same time the Long Short portfolio showed positive yearly abnormal returns of 0,83% using the FF5FM, which, however, was not statistically significant.

- *How did ESG investments perform during stressed periods?*

The study indicates that during the Covid-19 period, both the Long Best in Class portfolio and the Long Short portfolio yielded positive Annual Average Returns. However, the Long Short portfolio outperformed in terms of risk-adjusted returns (ISR), driven by lower volatility resulting from reduced exposure in the market. This reduction stemmed from balanced long and short positions, which mitigated potential upsides but also decreased the downside of the stock market downturn. In contrast, during the same period, the Long Worst in Class portfolio reported negative annual average returns and exhibited the highest volatility, and MDD.

Transitioning to the Russia-Ukraine War period, only the Long Short portfolio generated positive annual average returns, reporting the lowest volatility and MDD among the three strategies, owing to the same factors observed during the Covid-19 period. Conversely, the Long Best in Class and Long Worst in Class portfolios both experienced negative annual average returns due to a slower recovery in the stock market.

- *Did ESG investments produce abnormal returns during crisis periods?*

The empirical results obtained through OLS regression analysis with the CAPM, FF3FM, and FF5FM reveal that while the Long Best in Class portfolio demonstrated negative abnormal returns for both the Covid-19 period and the Russia-Ukraine War period, and the Long Short portfolio exhibited positive abnormal returns for the two periods, none of the results obtained with the OLS estimator provide evidence that investing in ESG investments yields abnormal returns, as the alpha observed in the two portfolios is never statistically significant.

Several limitations must be considered when interpreting the findings of this study. One of the critical factors is the analysis of a single subset of U.S.-domiciled companies, namely the Russell 3000. Another limitation is associated with the fact that the study considered an equal weighting of the companies in which each portfolio. However, an analysis incorporating a market cap-weighted approach or a mean-reverting approach, weighting more companies that are further away from their mean, would offer a more comprehensive analysis. Lastly, the study excludes transaction costs. Indeed, acknowledging that transaction costs negatively impact the returns achieved by the portfolios, and that portfolios like the Long Short are particularly exposed to this cost as transactions on short positions are more expensive for ideal investors, this poses significant limitations to the conclusions drawn and the abnormal returns observed.

# 6. References


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# 7. Appendix

*Exhibit 1: Cumulative Performance, Entire Period*

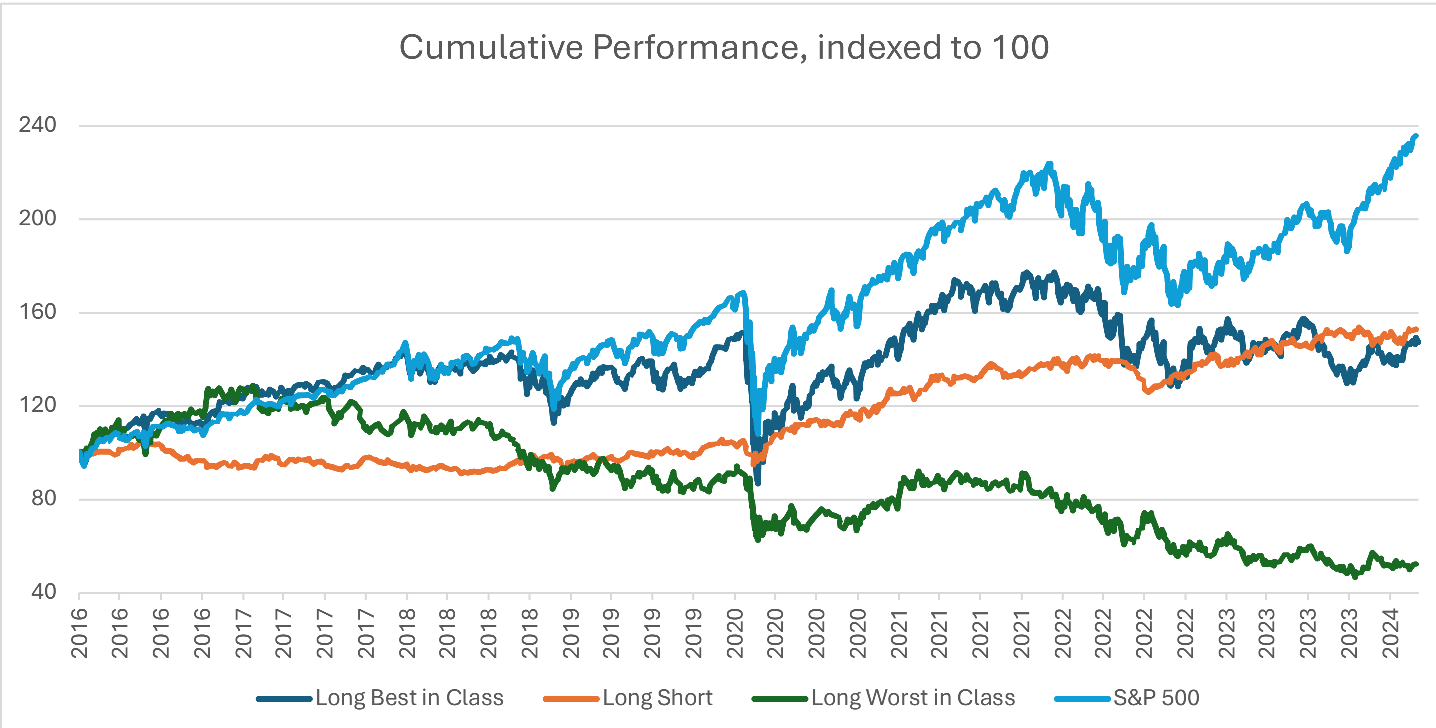



*Table 1: Comparative Metrics, Entire Period*

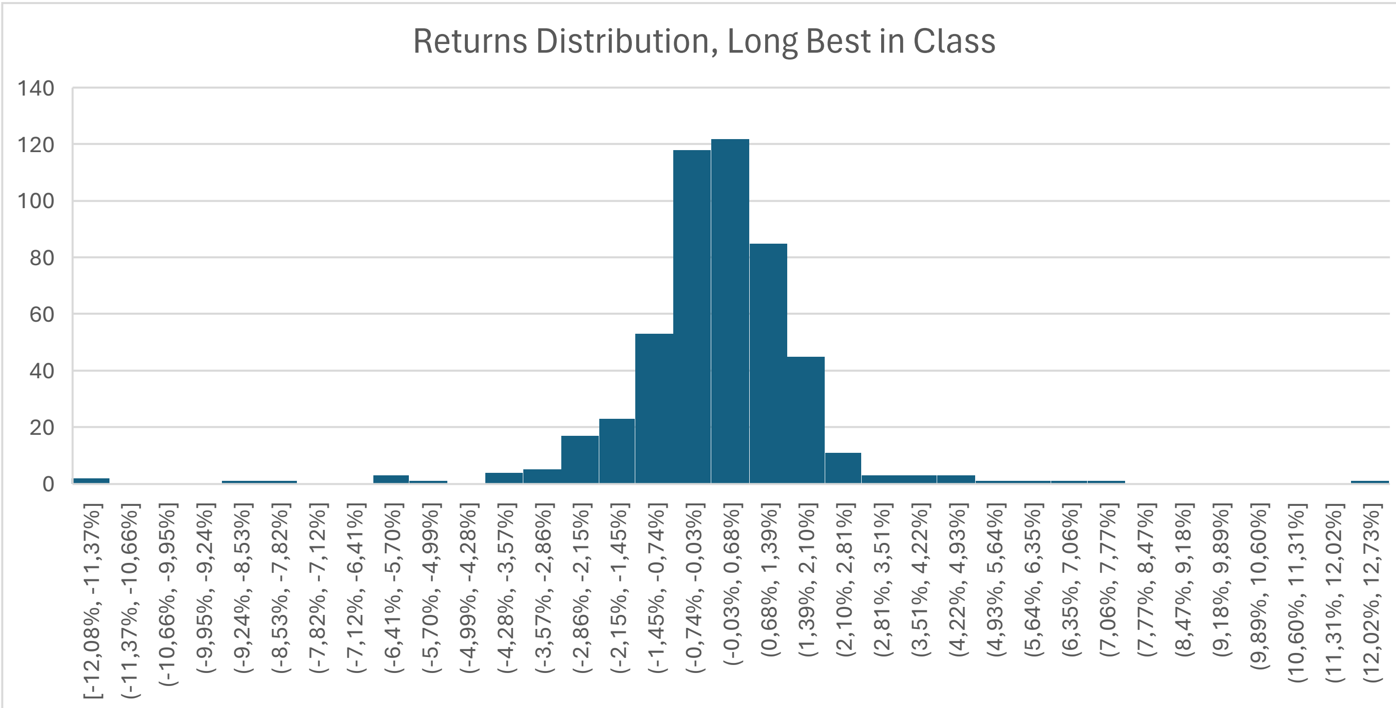
| | Long Best in Class | Long Short | Long Worst in Class | S&P 500 |
|---|---|---|---|---|
| **Annual Geometric Return** | 4,87% | 5,29% | -7,70% | 11,07% |
| **Annual Average Return** | 7,02% | 5,67% | -5,46% | 12,99% |
| **Annual Standard Deviation** | 20,08% | 8,50% | 21,89% | 18,46% |
| **Info Sharpe Ratio** | 0,3497 | 0,6673 | -0,2493 | 0,7036 |
| **Skewness** | -0,7093 | 0,1848 | -0,2400 | -0,8656 |
| **Kurtosis** | 16,2280 | 4,3967 | 3,5401 | 16,8053 |
| **Max Drawdown** | -43% | -13,58% | -63,76% | -36,10% |

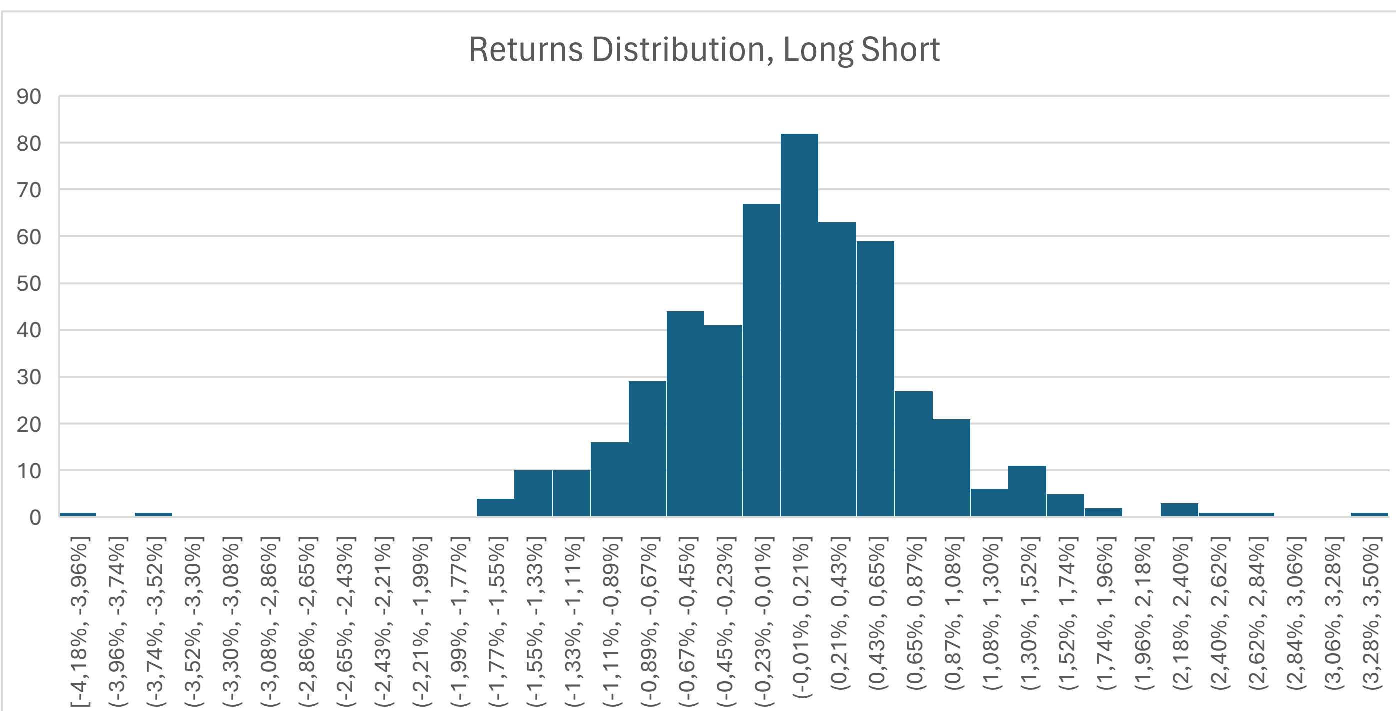
*Exhibit 2: Cumulative Performance, Covid-19*


*Table 2: Comparative Metrics, Covid-19*

| | Long Best in Class | Long Short | Long Worst in Class |
|---|---|---|---|
| **Annual Geometric Return** | 10,22% | 11,06% | -11,68% |
| **Annual Average Return** | 15,00% | 11,83% | -7,54% |
| **Annual Standard Deviation** | 28,99% | 11,81% | 30,11% |
| **Info Sharpe Ratio** | 0,517363655 | 1,001829115 | -0,250283977 |
| **Skewness** | -0,807270127 | -0,151455207 | -0,958439604 |
| **Kurtosis** | 14,21395326 | 4,05471908 | 9,705768287 |
| **Max Drawdown** | -43,44% | -9,20% | -43,36% |

*Exhibit 3: Returns Distributions, Covid-19*



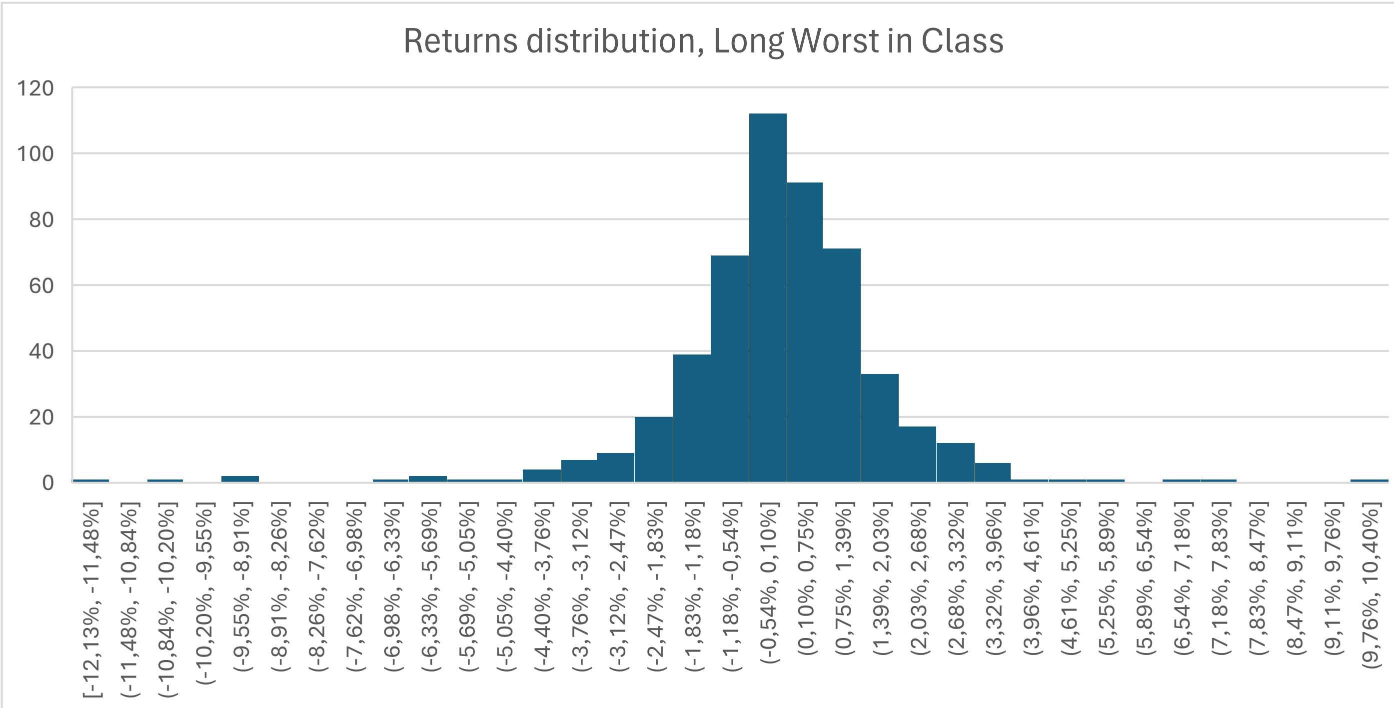



*Exhibit 4: Cumulative Performance, Russia-Ukraine War*

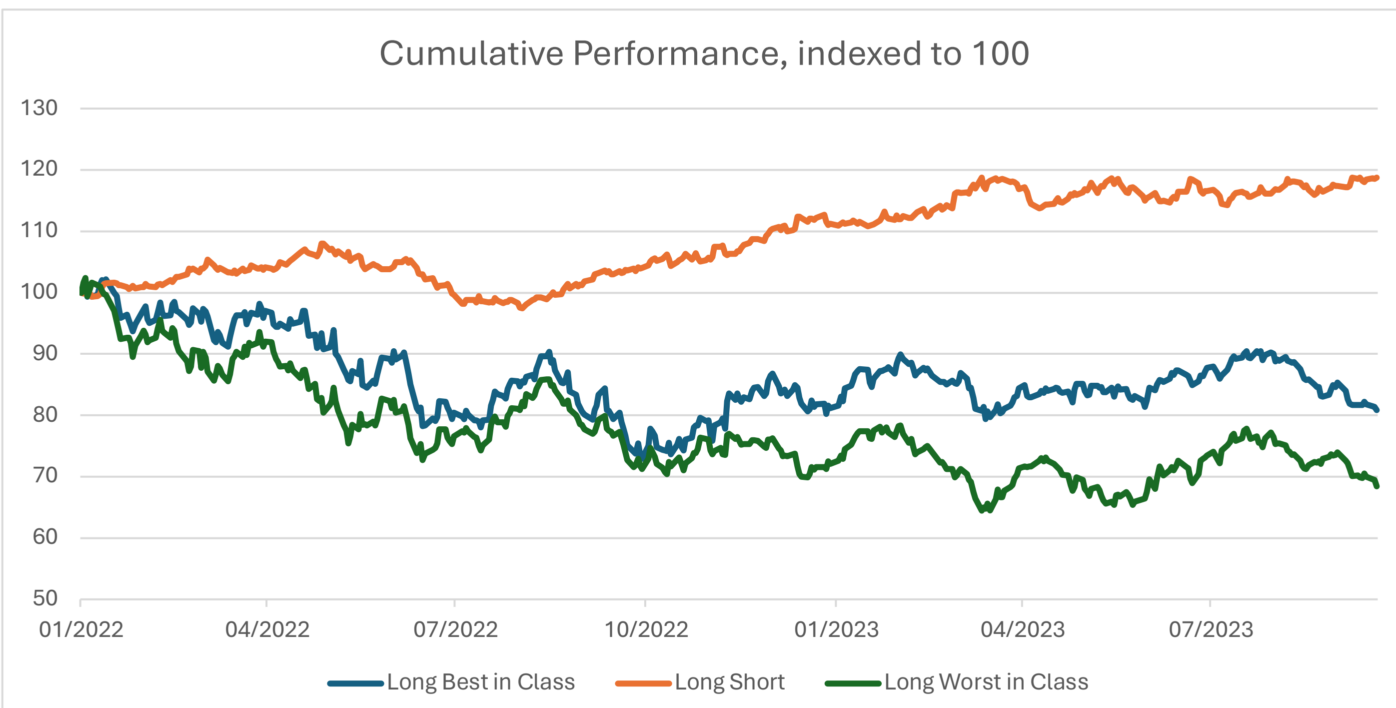
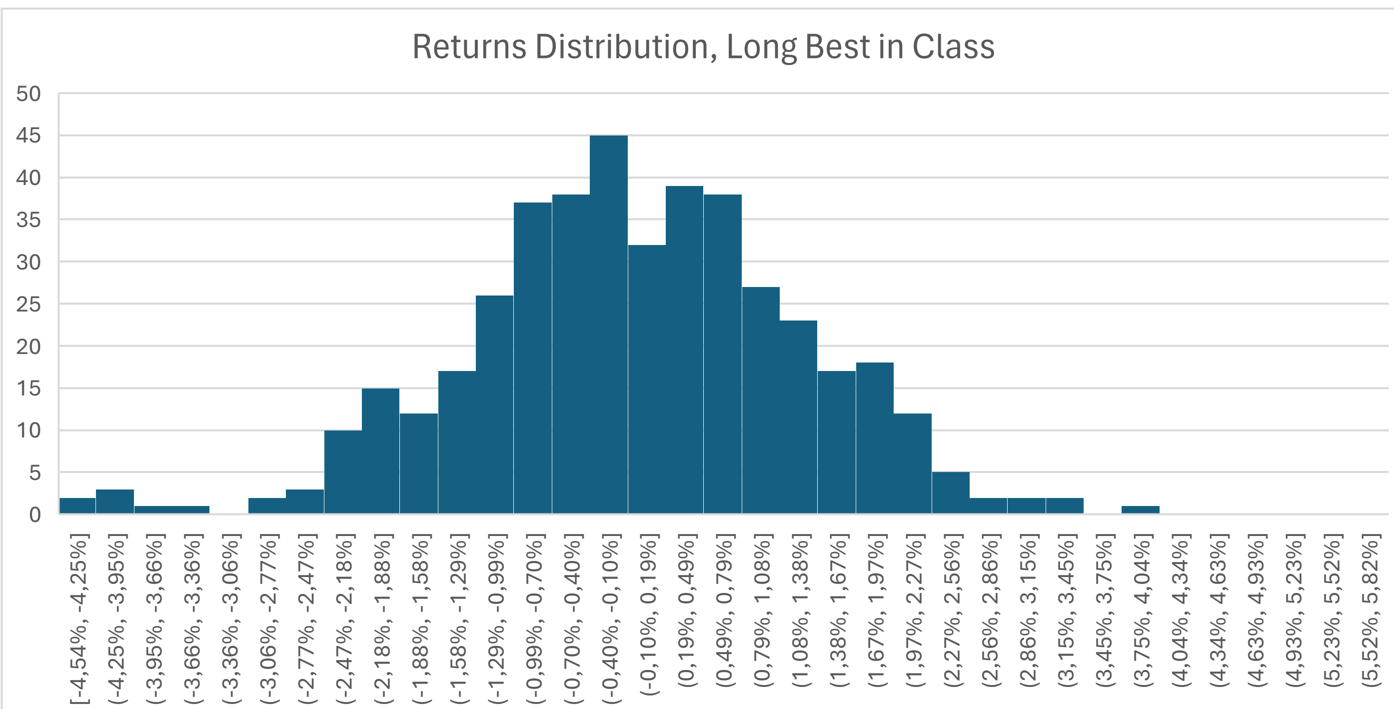
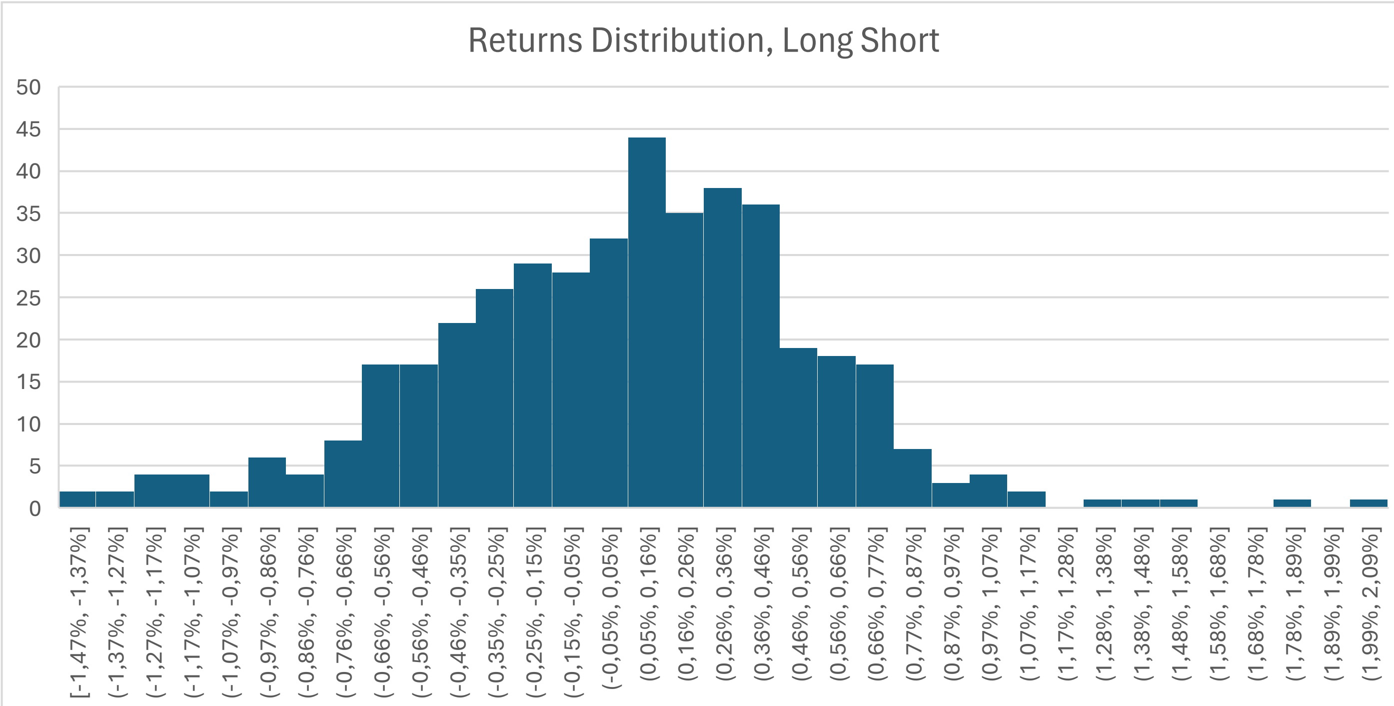


*Table 3: Comparative Metrics, Russia-Ukraine War*

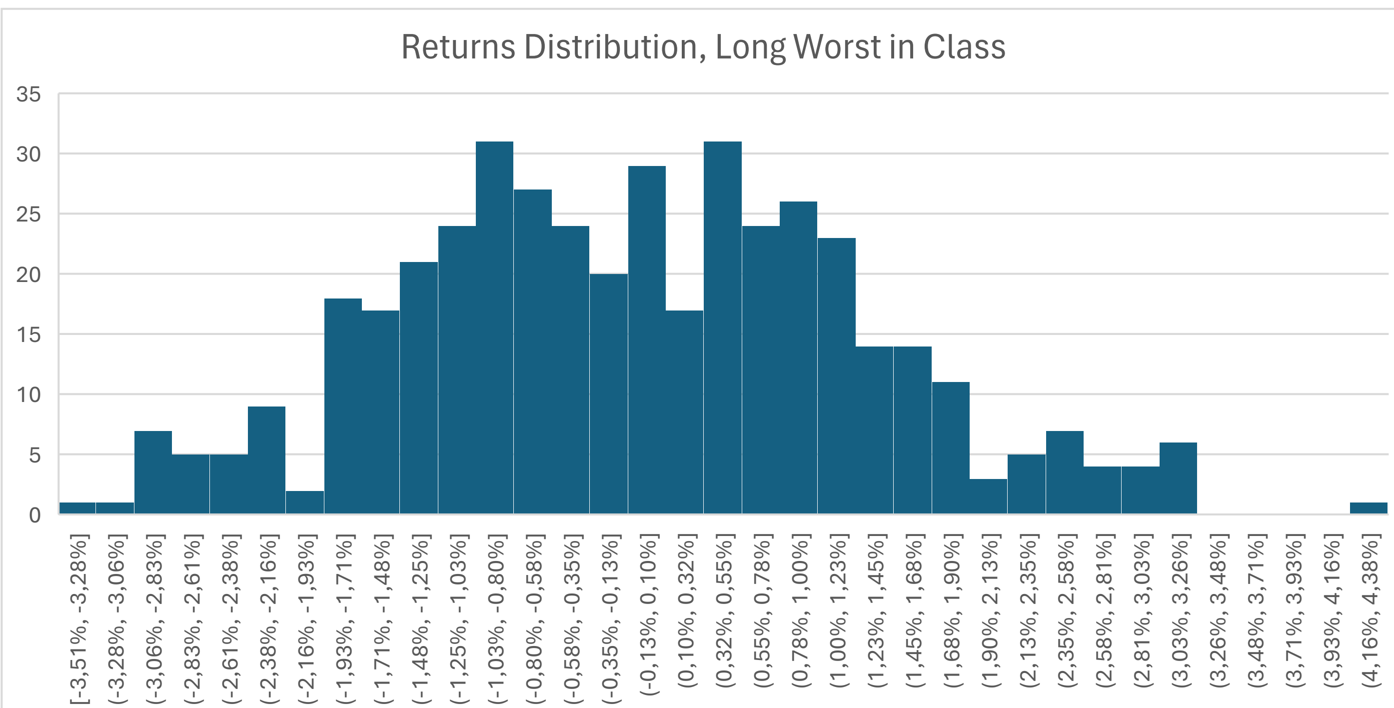
| | Long Best in Class | Long Short | Long Worst in Class |
|---|---|---|---|
| **Annual Geometric Return** | -11,68% | 10,54% | -19,90% |
| **Annual Average Return** | -9,66% | 10,89% | -19,86% |
| **Annual Standard Deviation** | 21,30% | 7,99% | 21,62% |
| **Info Sharpe Ratio** | -0,4536 | 1,3626 | -0,9184 |
| **Skewness** | -0,0720 | -0,0689 | 0,1752 |
| **Kurtosis** | 1,1072 | 0,9889 | -0,1858 |
| **Max Drawdown** | -28,64% | -9,81% | -37,01% |

*Exhibit 5: Returns Distributions Russia-Ukraine War*





Returns Distribution, Long Short

Returns Distribution, Long Worst in Class

*Exhibit 6: Cumulative Performance, Pre-Covid-19 Crisis*

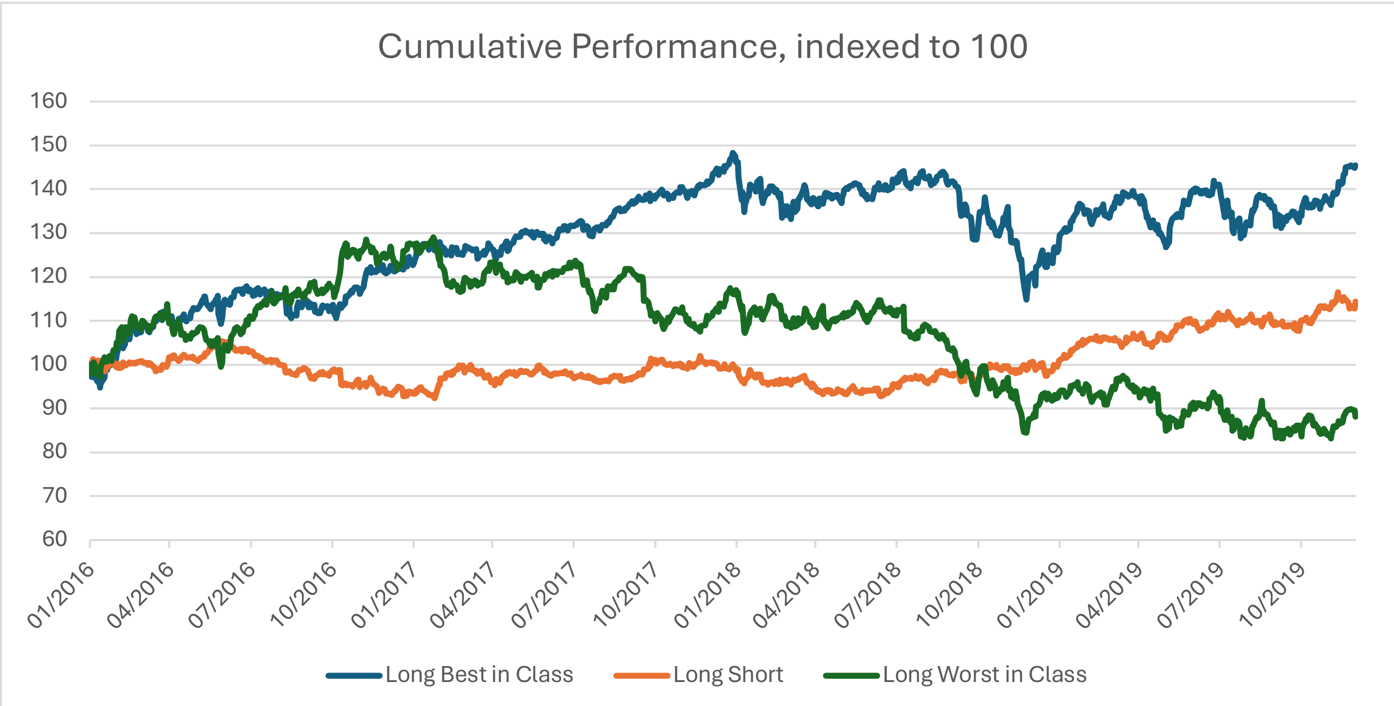
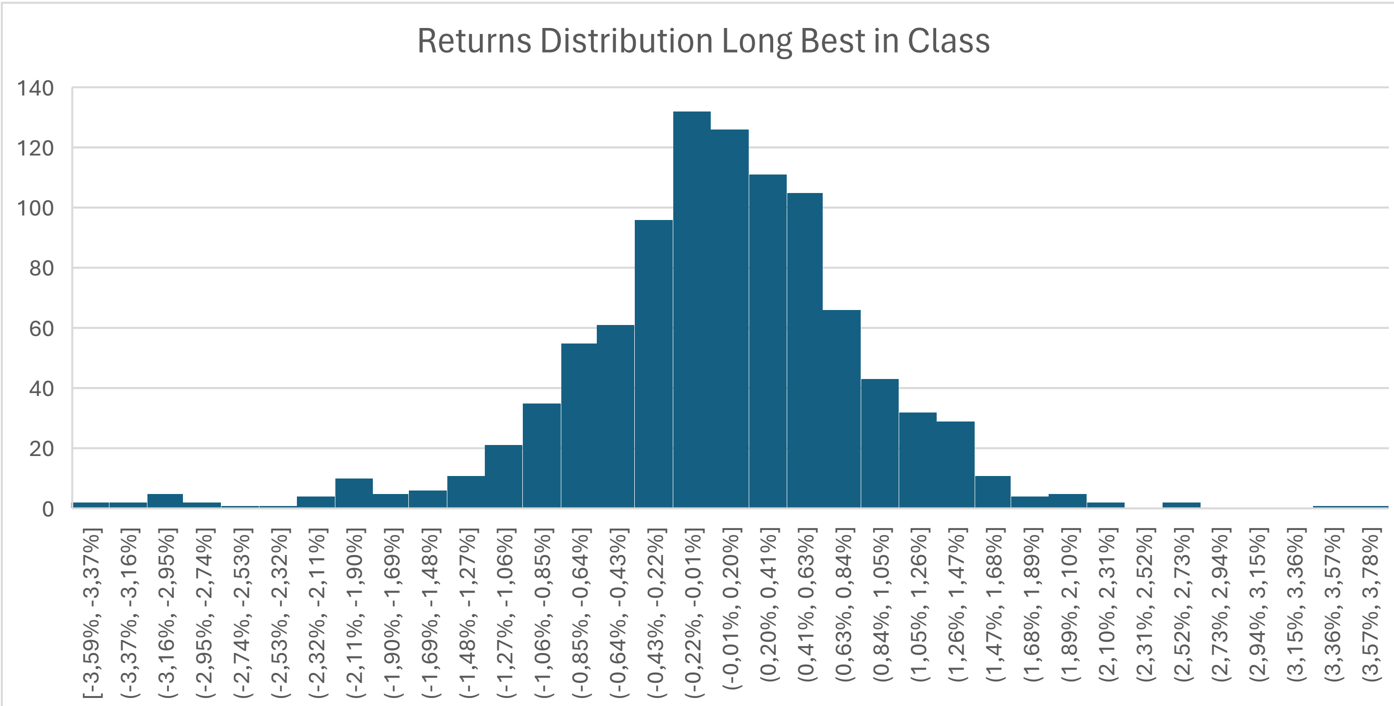
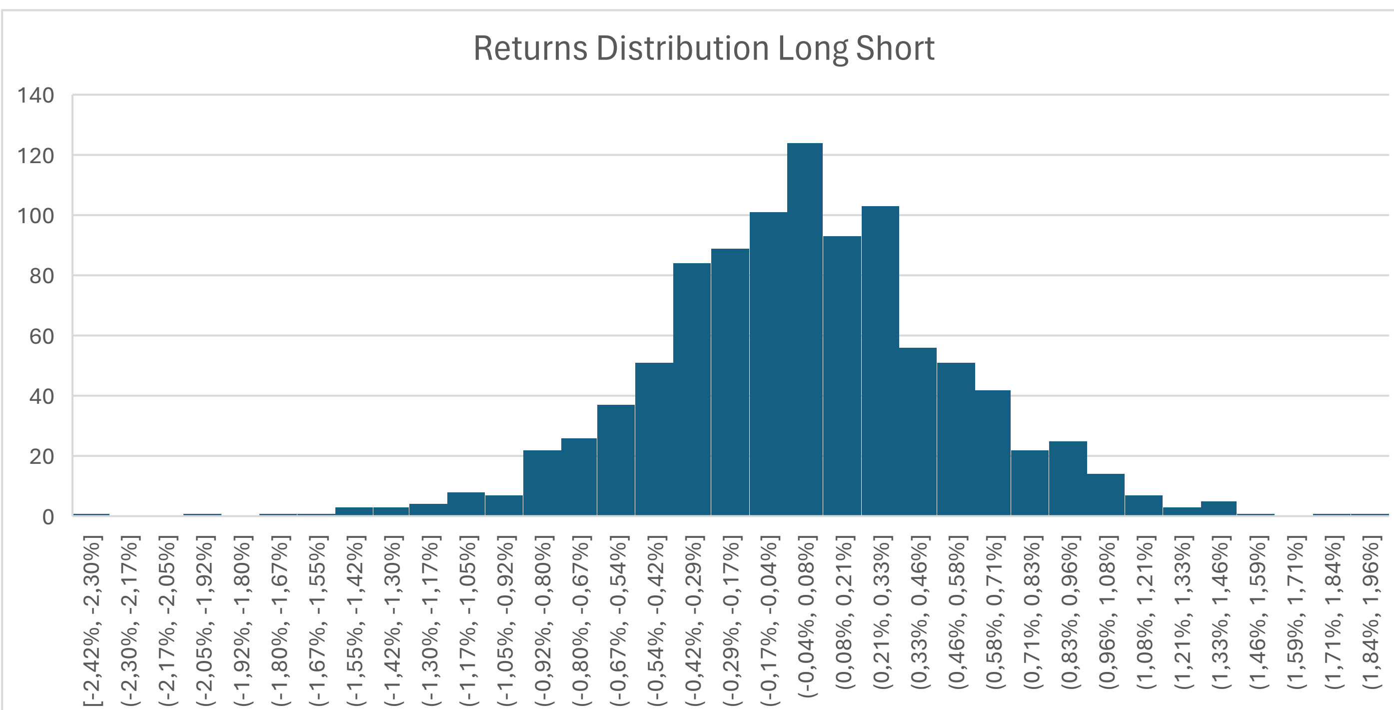



*Table 4: Comparative Metrics, Pre-Covid-19 Period*

| | Long Best in Class | Long Short | Long Worst in Class |
|---|---|---|---|
| **Annual Geometric Return** | 10,05% | 3,50% | -3,18% |
| **Annual Average Return** | 10,99% | 3,83% | -2,04% |
| **Annual Standard Deviation** | 13,04% | 7,99% | 15,28% |
| **Info Sharpe Ratio** | 0,8427 | 0,479635016 | -0,13367754 |
| **Skewness** | -0,5305 | -0,109620658 | -0,399362629 |
| **Kurtosis** | 2,7835 | 1,257450525 | 1,739026874 |
| **Max Drawdown** | -22,57% | -12,34% | -35,56% |

*Exhibit 7: Returns Distributions, Pre-Covid-19 Period*



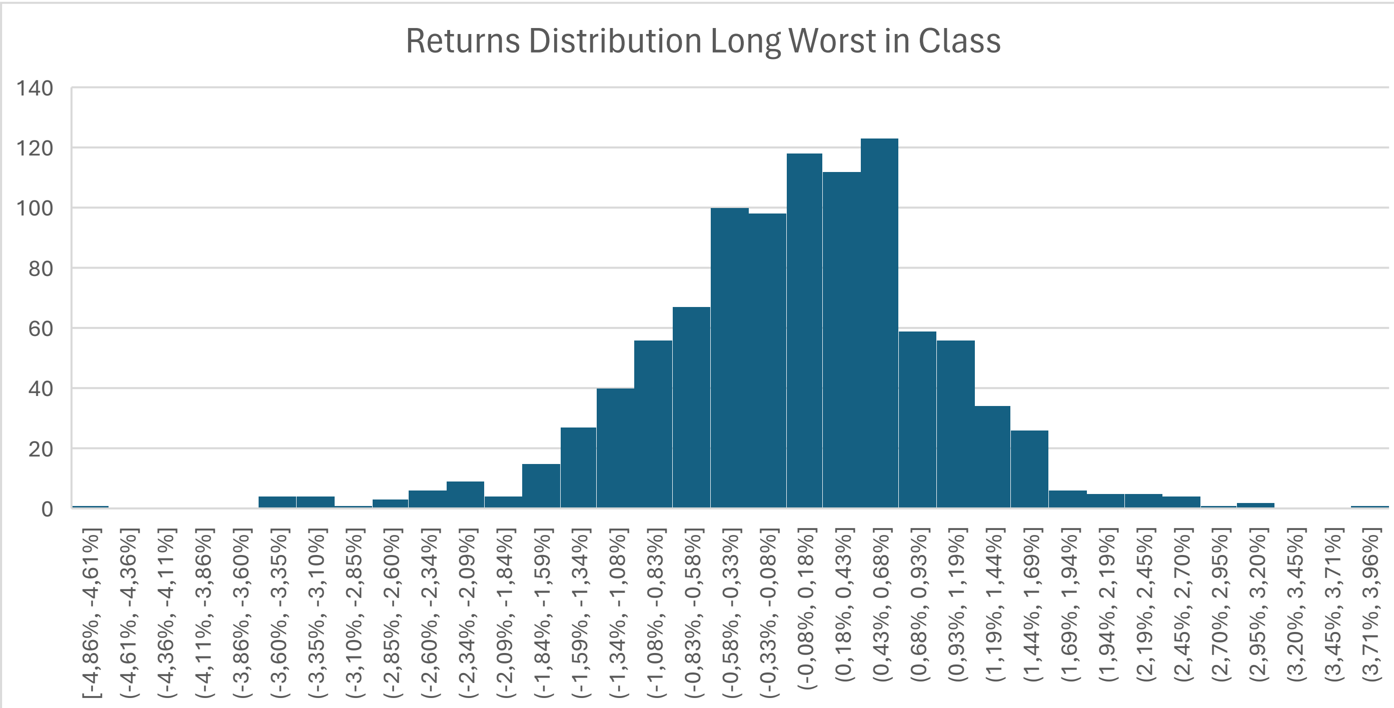



*Exhibit 8: CAPM, Entire Period*

**CAPM Long Best**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,90 |
| **R Square** | **0,82** |
| Adjusted R Square | 0,81 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | 0,005 |
| Mkt-RF | 0,960 | 0,000 |
| **Daily Alpha** | **-0,03%** | |
| **Yearly Alpha** | **-8,50%** | |

**CAPM Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,24 |
| **R Square** | **0,06** |
| Adjusted R Square | 0,06 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | 0,462 |
| Mkt-RF | 0,110 | 0,000 |
| **Daily Alpha** | **0,01%** | |
| **Yearly Alpha** | **2,14%** | |

**CAPM Long Worst**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,75 |
| **R Square** | **0,56** |
| Adjusted R Square | 0,56 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | -0,001 | 0,000 |
| Mkt-RF | 0,866 | 0,000 |
| **Daily Alpha** | **-0,08%** | |
| **Yearly Alpha** | **-19,06%** | |

## *Exhibit 9: Fama-French 3 Factor Model, Entire Period*

**FF3 Long Best**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,92 |
| **R Square** | **0,85** |
| Adjusted R Square | 0,85 |
| Standard Error | 0,00 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | 0,004 |
| Mkt-RF | 0,948 | 0,000 |
| SMB | 0,179 | 0,000 |
| HML | 0,230 | 0,000 |
| **Daily Alpha** | **-0,03%** | |
| **Yearly Alpha** | **-7,83%** | |

**FF3 Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,29 |
| **R Square** | **0,08** |
| Adjusted R Square | 0,08 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | 0,514 |
| Mkt-RF | 0,126 | 0,000 |
| SMB | -0,124 | 0,000 |
| HML | 0,015 | 0,201 |
| **Daily Alpha** | **0,01%** | |
| **Yearly Alpha** | **1,87%** | |

**FF3 Long Worst**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,82 |
| **R Square** | **0,67** |
| Adjusted R Square | 0,67 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | -0,001 | 0,000 |
| Mkt-RF | 0,804 | 0,000 |
| SMB | 0,594 | 0,000 |
| HML | 0,262 | 0,000 |
| **Daily Alpha** | **-0,07%** | |
| **Yearly Alpha** | **-17,40%** | |

## *Exhibit 10: Fama-French 5 Factor Model, Entire Period*

**FF5 Long Best**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,93 |
| **R Square** | **0,86** |
| Adjusted R Square | 0,86 |
| Standard Error | 0,00 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | 0,002 |
| Mkt-RF | 0,966 | 0,000 |
| SMB | 0,222 | 0,000 |
| HML | 0,118 | 0,000 |
| RMW | 0,062 | 0,006 |
| CMA | 0,175 | 0,000 |
| **Daily Alpha** | **-0,03%** | |
| **Yearly Alpha** | **-8,42%** | |

**FF5 Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,33 |
| **R Square** | **0,11** |
| Adjusted R Square | 0,11 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,768** |
| Mkt-RF | 0,149 | 0,000 |
| SMB | -0,063 | 0,001 |
| HML | -0,053 | 0,002 |
| RMW | 0,149 | 0,000 |
| CMA | 0,170 | 0,000 |
| **Daily Alpha** | **0,00%** | |
| **Yearly Alpha** | **0,83%** | |

**FF5 Long Worst**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,82 |
| **R Square** | **0,68** |
| Adjusted R Square | 0,68 |
| Standard Error | 0,01 |
| Observations | 2034 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | -0,001 | 0,000 |
| Mkt-RF | 0,781 | 0,000 |
| SMB | 0,556 | 0,000 |
| HML | 0,210 | 0,000 |
| RMW | -0,115 | 0,002 |
| CMA | -0,132 | 0,007 |
| **Daily Alpha** | **-0,07%** | |
| **Yearly Alpha** | **-16,53%** | |

*Exhibit 11: CAPM, Covid-19*

| CAPM Long Best | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,92 |
| **R Square** | **0,85** |
| Adjusted R Square | 0,84 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,169** |
| Mkt-RF | 1,013 | 0,000 |
| **Daily Alpha** | **-0,04%** | |
| **Yearly Alpha** | **-11,13%** | |

| CAPM Long Short | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,41 |
| **R Square** | **0,17** |
| Adjusted R Square | 0,17 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,401** |
| Mkt-RF | 0,186 | 0,000 |
| **Daily Alpha** | **0,03%** | |
| **Yearly Alpha** | **6,41%** | |

*Exhibit 12: Fama-French 3 Factor Model, Covid-19*

| FF3 Long Best | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,94 |
| **R Square** | **0,89** |
| Adjusted R Square | 0,89 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,180** |
| Mkt-RF | 0,963 | 0,000 |
| SMB | 0,144 | 0,000 |
| HML | 0,256 | 0,000 |
| **Daily Alpha** | **-0,04%** | |
| **Yearly Alpha** | **-9,10%** | |

| FF3 Long Short | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,44 |
| **R Square** | **0,19** |
| Adjusted R Square | 0,19 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,345** |
| Mkt-RF | 0,193 | 0,000 |
| SMB | -0,123 | 0,001 |
| HML | 0,016 | **0,458** |
| **Daily Alpha** | **0,028%** | |
| **Yearly Alpha** | **7,134%** | |

*Exhibit 13: Fama-French 5 Factor Model, Covid-19*

FF5 Long Best

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,95 |
| **R Square** | **0,90** |
| Adjusted R Square | 0,89 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,157** |
| Mkt-RF | 0,978 | 0,000 |
| SMB | 0,150 | 0,000 |
| HML | 0,168 | 0,000 |
| RMW | -0,036 | **0,492** |
| CMA | 0,286 | 0,000 |
| **Daily Alpha** | **-0,04%** | |
| **Yearly Alpha** | **-9,49%** | |

FF5 Long Short

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,46 |
| **R Square** | **0,22** |
| Adjusted R Square | 0,21 |
| Standard Error | 0,01 |
| Observations | 505 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,580** |
| Mkt-RF | 0,193 | 0,000 |
| SMB | -0,050 | **0,214** |
| HML | -0,017 | **0,607** |
| RMW | 0,223 | 0,000 |
| CMA | -0,056 | **0,451** |
| **Daily Alpha** | **0,016%** | |
| **Yearly Alpha** | **4,148%** | |

*Exhibit 14: CAPM, Russia-Ukraine War*

CAPM Long Short

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,12 |
| **R Square** | **0,01** |
| Adjusted R Square | 0,01 |
| Standard Error | 0,01 |
| Observations | 431 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,0003 | **0,2005** |
| Mkt-RF | 0,0447 | 0,0132 |
| **Daily Alpha** | **0,03%** | |
| **Yearly Alpha** | **7,79%** | |

*Exhibit 15: Fama-French 3 Factor Model, Russia-Ukraine War*

| FF3 Long Short | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,23 |
| **R Square** | **0,05** |
| Adjusted R Square | 0,05 |
| Standard Error | 0,00 |
| Observations | 431 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,0003 | **0,2438** |
| Mkt-RF | 0,0871 | 0,0000 |
| SMB | -0,1020 | 0,0112 |
| HML | 0,0642 | 0,0143 |
| **Daily Alpha** | **0,028%** | |
| **Yearly Alpha** | **6,970%** | |

*Exhibit 16: Fama-French 5 Factor, Russia-Ukraine War*

| FF5 Long Short | |
|---|---|
| *Regression Statistics* | |
| Multiple R | 0,28 |
| **R Square** | **0,08** |
| Adjusted R Square | 0,07 |
| Standard Error | 0,00 |
| Observations | 431 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,0003 | **0,2598** |
| Mkt-RF | 0,1082 | 0,0000 |
| SMB | -0,0704 | **0,1158** |
| HML | -0,0065 | **0,8655** |
| RMW | -0,0148 | **0,7149** |
| CMA | 0,2065 | 0,0005 |
| **Daily Alpha** | **0,026%** | |
| **Yearly Alpha** | **6,664%** | |

*Exhibit 17: CAPM, Pre-Covid-19 Period*

**CAPM Long Best**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,88 |
| **R Square** | **0,77** |
| Adjusted R Square | 0,77 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,200** |
| Mkt-RF | 0,882 | 0,000 |
| **Daily Alpha** | **-0,02%** | |
| **Yearly Alpha** | **-4,04%** | |

**CAPM Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,19 |
| **R Square** | **0,04** |
| Adjusted R Square | 0,04 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,853** |
| Mkt-RF | 0,117 | 0,000 |
| **Daily Alpha** | **0,00%** | |
| **Yearly Alpha** | **0,74%** | |

*Exhibit 18: Fama-French 3 Factor Model, Pre-Covid-19 Period*

**FF3 Best in Class**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,88 |
| **R Square** | **0,78** |
| Adjusted R Square | 0,78 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,249** |
| Mkt-RF | 0,882 | 0,000 |
| SMB | 0,070 | 0,005 |
| HML | 0,131 | 0,000 |
| **Daily Alpha** | **-0,01%** | |
| **Yearly Alpha** | **-3,75%** | |

**FF3 Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,29 |
| **R Square** | **0,08** |
| Adjusted R Square | 0,08 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,991** |
| Mkt-RF | 0,130 | 0,000 |
| SMB | -0,169 | 0,000 |
| HML | -0,124 | 0,000 |
| **Daily Alpha** | **0,00%** | |
| **Yearly Alpha** | **0,04%** | |

*Exhibit 19: Fama-French 5 factor Model, Pre-Covid-19 Period*

**FF5 Best in Class**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,89 |
| **R Square** | **0,80** |
| Adjusted R Square | 0,79 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,165** |
| Mkt-RF | 0,924 | 0,000 |
| SMB | 0,077 | 0,001 |
| HML | 0,014 | **0,574** |
| RMW | 0,100 | 0,005 |
| CMA | 0,330 | 0,000 |
| **Daily Alpha** | **-0,02%** | |
| **Yearly Alpha** | **-4,17%** | |

**FF5 Long Short**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0,31 |
| **R Square** | **0,10** |
| Adjusted R Square | 0,09 |
| Standard Error | 0,00 |
| Observations | 987 |

| | *Coefficients* | *P-value* |
|---|---|---|
| Intercept | 0,000 | **0,910** |
| Mkt-RF | 0,161 | 0,000 |
| SMB | -0,161 | 0,000 |
| HML | -0,160 | 0,000 |
| RMW | 0,125 | 0,006 |
| CMA | 0,183 | 0,001 |
| **Daily Alpha** | **0,00%** | |
| **Yearly Alpha** | **-0,44%** | |

*Exhibit 20: Value Inflation Factor (VIF) FF5FM, Covid-19*

| **VIF FF5FM** | |
|---|---|
| **Mkt-RF** | 1,10752446 |
| **SMB** | 1,74963039 |
| **HML** | 2,52642674 |
| **RMW** | 1,71647111 |
| **CMA** | 1,61026192 |

**Correlation Table**

| | *CMA* | *RMW* | *HML* | *SMB* | *Mkt-RF* |
|---|---|---|---|---|---|
| CMA | 1 | | | | |
| RMW | 0,4193282 | 1 | | | |
| HML | 0,55847792 | 0,45264295 | 1 | | |
| SMB | 0,18439742 | -0,1591415 | 0,4887889 | 1 | |
| Mkt-RF | -0,092929 | 0,00543212 | 0,17627727 | 0,20659383 | 1 |

*Exhibit 21: Value Inflation Factor (VIF) FF5FM, Russia-Ukraine War*

| **VIF FF5FM** | |
|---|---|
| Mkt-RF | 1,50898428 |
| SMB | 1,31534962 |
| HML | 3,07932271 |
| RMW | 1,57972512 |
| CMA | 3,26103687 |

**Correlation Table**

| | *Mkt-RF* | *SMB* | *HML* | *RMW* | *CMA* |
|---|---|---|---|---|---|
| Mkt-RF | 1 | | | | |
| SMB | 0,20946607 | 1 | | | |
| HML | -0,472497 | -0,0847561 | 1 | | |
| RMW | -0,3662875 | -0,4112568 | 0,4666579 | 1 | |
| CMA | -0,5636342 | -0,2389167 | 0,79318565 | 0,43470643 | 1 |

*Exhibit 22: Value Inflation Factor (VIF) FF3FM, Russia-Ukraine War*

| VIF FF3FFM | |
|---|---|
| Mkt-RF | 1,33719142 |
| SMB | 1,04617417 |
| HML | 1,2877716 |

**Correlation Table**

| | *HML* | *SMB* | *Mkt-RF* |
|---|---|---|---|
| HML | 1 | | |
| SMB | -0,0847561 | 1 | |
| Mkt-RF | -0,472497 | 0,20946607 | 1 |