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ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

Value, Distress, and Short-Term Reversal

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Title

Analysis Of Quantitative Investment Strategies: Value, Distress, and Short-Term Reversal

Abstract

This report aims to analyze the performance of a long-short investment strategy over a 12-year sample period. The strategy is constructed upon the approach of Fama and French (1992) to value investing and the *marginality* of firms, as advanced by Chan and Chen (1991). A short-term reversal component is subsequently implemented to take advantage of the interplay between value and marginality. Notwithstanding considerable barriers to its implementation, and while past returns do not necessarily predict future returns, the strategy delivers the best risk-adjusted return relative to considered benchmarks, averaging an annual return of 12.47% and 9.54% of annual volatility.

Keywords

Finance; Financial Markets; Financial or Data Analysis; Portfolio Optimization

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1. Introduction

The findings of Kenneth French and Eugene Fama in their seminal paper *Cross-Section of Expected Stock Returns* (Fama and French 1992) continue to enjoy relevance in the 21st century's financial academia and broader financial sector. Drawing on the principle of rational (efficient) markets, the Fama-French Three Factor Model, a significant extension of the Capital Asset Pricing Model, sought to explain stock returns by measuring how they responded relative to factors – the High Minus Low (HML) and Small Minus Big (SMB) factors, in particular. To this extent, the authors formed portfolios on size - measured by Market Equity (price times shares outstanding) - and further broke them down according to Book-to-Market (equity) ratios. The portfolios whose Market Equity sat above the median Market Equity, deemed big portfolios, were found to underperform relative to their small, below-median counterparts. On the other hand, portfolios containing stocks with the highest Book-to-Market ratios were found to overperform relative to their counterparts with low Book-to-Market ratios. Portfolios on opposite ends of the Book-to-Market spectrum are then combined into a single, long-short strategy: *High* portfolios are held indefinitely, while *Low* portfolios are sold short.

Table 1 - Fama/ French (1992) Factor Construction

Size (ME) breakpoint Median Market Equity (ME)		**Book-to-Market (BE/ME) breakpoints**
Small Value	Big Value	70%
Small Neutral	Big Neutral	
Small Growth	Big Growth	30%
SMB = 1/3 (Small Value + Small Neutral + Small Growth - 1/3 (Big Value + Big Neutral + Big Growth)		
HML =1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth)		

The explanations – and implications – of these findings have been the source of intense debate over the last three decades. According to the traditional explanation by Fama and French, the market judges low stock prices relative to book value as an indicator of poor earnings prospects. The relative distress factor of Chan and Chen (1991) encapsulates this argument well: the authors postulate that marginal firms, whose stock prices have fallen over time because of persistently poor performance, are more likely to shrink in relative size and suffer from high financial leverage (defined as the sum of book value of current liabilities, long term debt, and preferred stock over market value of equity). Should companies continue to perform poorly, shrinking further, and should they fail to change their capital structure accordingly, they will likely suffer from market-imposed financial leverage, as the market keeps discounting its stock price relative to its book value (which widens the gap between book and market equities). Marginal firms can therefore have a hard time navigating periods of economic uncertainty and be particularly constrained during times of monetary tightening (credit is scarce and more expensive). Finally, and perhaps most significantly, the authors ascribe to the idea that it is not size *per se* that explains the risk-return profile of firms of *big* and *small* firms, but rather characteristics, like cash flow problems or operational inefficiencies, that make them *marginal* and thus more sensitive to changes in the economy. Marginal firms tend to be more concentrated in portfolios comprised of small stocks, which is why the latter are said to be riskier and to offer correspondingly higher returns.

This economic rationale, and the interplay between *marginality* and book-to-market, within the Fama and French (1992) portfolio construction framework, is the groundwork upon which my investment strategy is built. In the following sections, I will briefly introduce the investment strategy, outlining its construction and discussing its performance. I will subsequently describe the portfolio construction methodology and touch upon the limitations of the strategy, finishing the report with a succinct conclusion.

2. Strategy overview

As certain stocks appear to behave in a chronically marginal way (Chan and Chen 1991), I found it interesting to test to what extent a short-term reversal strategy could be compatible with Chan and Chen's findings. First proposed by Jegadeesh (Jegadeesh 1990), a standard short-term reversal is a zero-investment strategy that consists of sorting stocks into deciles based on prior-month returns, buying stocks in the bottom decile (losers) and selling stocks in the top decile (winners). To this extent, and deploying a new analytical decomposition of short-term reversal profits, a staff report from the Federal Reserve of New York (Da, Qianqiu and Schaumburg 2011) sought to reconcile two competing, albeit not mutually exclusive explanations of short-term reversal profits:

1. On the one hand, Shiller (1984) and Stiglitz (1989), among others, have argued that short-term reversal profits are driven by investor overreaction to information, or simply cognitive errors (the sentiment-based explanation).
2. On the other hand, authors like Grossman and Miller (1988) have described short-term reversal profits as compensation for liquidity providers during periods of larger spreads between supply and demand (when supply and demand curves move in opposite directions). This is deemed the liquidity-based explanation.

Da et. al (2011) first decompose short-term reversal profits into an across-industry and within-industry components. As Moskowitz and Grinblatt (1999) pointed out, there is a strong industry momentum, whereby current winner industries outperform current loser industries in subsequent months, implying that, on average, this component contributes negatively to short-term reversal profits. The within-industry component therefore remains as the positive contributor: in other words, investors overact to firm-specific news bur underreact to industry-specific news. To this extent, Da et. al (2011) break down the within-industry component into four components: (1) within-industry variation in expected returns, (2) under- or overreaction to within-industry cash flow shocks and (3) a residual component.

While the first two components are negative, only the second is significant, which is consistent with the vastly-document earnings momentum observed by Chan et al. (1996). The residual component, however, is significantly positive. Moreover, and most importantly for the object of this thesis, this residual component – that encompasses all changes in stock prices driven by 'nonfundamental' factors/ variables - holds for subsamples constructed on characteristics such as size, book-to-market, or liquidity, and can withstand several robustness checks. It is positive and (statistically) significant even among the largest and most liquid stocks in the (comprehensive, non-penny and analyst-covered) sample the authors used to conducts their analysis. Drawing on a modified short-term reversal strategy (which sorts stocks based on prior-month discount rate[1] news), the authors account for the residual component and effectively reconcile the previously-mentioned explanations for short-term reversal profits:

1. The profits from buying losers relate positively and significantly with the lagged aggregate Amihud (2002) illiquidity measure; the higher the level of illiquidity, the larger the profits, which hints at compensation for liquidity provision on the buy-side (buy-side pressure jacks up prices).
2. The profits from selling winners relate positively and significantly with two lagged measures of investor optimism and equity overvaluation - monthly number of IPOs and monthly equity share in new issues (Baker and Wurgler 2006) -, which comprise an aggregate measure of overvaluation (optimistic investor sentiment).

[1] '(The discount rate) refers to the interest rate used in discounted cash flow (DCF) analysis to determine the present value of future cash flows (and hence the Enterprise Value).' (Via *Investopedia*). It corresponds to the residual component in the authors' model.

In short, liquidity shocks always seem to drive the reversal on recent losers (long side) while investor sentiment always seems to drive the reversal on recent winners (short side). To this extent, I constructed equal-weighted portfolios based on size and book-to-market ratios according to the original Fama French framework (thereby avoiding forward looking bias[2]), and then proceeded to sort them by their prior-month returns. My strategy ultimately rests on buying loser stocks that sit above the median size (market equity) breakpoint and within the uppermost book-to-market decile (90%), or bracket, and selling winner stocks that sit below the median size (market equity) breakpoint and within the bottommost book-to-market decile (10%), or bracket, within each industry. Long and short sides of the strategy have the same weight, which, in effect, renders the strategy a zero-investment strategy. Ultimately, the returns of the strategy are the difference between the long-side returns and short-side returns. However, the portfolio construction of my strategy differs from that of Fama and French insofar as:

1. The book-to-market breakpoints I used differ from those used by Fama and French (70% and 30%, respectively), more aggressively segregating stocks into value or growth portfolios, aiming to reinforce the validity of my strategy analysis.
2. The long side of the portfolio is *big,* whereas the short side is *small,* which runs counter to the idea that small stocks outperform large stocks:
    2.1. As marginal stocks are more common in portfolios comprised of small stocks relative to portfolios comprised of big stocks, I opted for the latter: in times of economic distress and uncertainty (like the financial crisis in 2008 or the damage wrought by the Covid-19 pandemic), as well as during prolonged periods of steady, albeit slow economic growth, a portfolio comprised of *big*

[2] "…a type of bias that occurs when a study or simulation relies on data or information that was not yet available or known during the time period being studied." (Via Corporate Finance Institute). Fama and French's approach bypasses this issue by lagging fundamental data relative to stock prices/ returns, in order to ensure such data is known to investors at the time of portfolio construction.

value stocks should be able to better withstand the pressure, offering lower volatility and thus rewarding the investor when most needed.

2.2. While big stocks are often more liquid, the profits of keeping winners within a portfolio comprised of *big value* stocks should be (albeit partially) driven by a measure of illiquidity (i.e., liquidity shocks should be responsible for part of the profits).

The fundamental attribute that underpins portfolio construction – the book-to-market ratio – is still assumed as the yardstick by which the quality of a stock is measured, which does not therefore mean a departure from Fama and French's original framework. Please find a visual representation of the strategy in the table below:

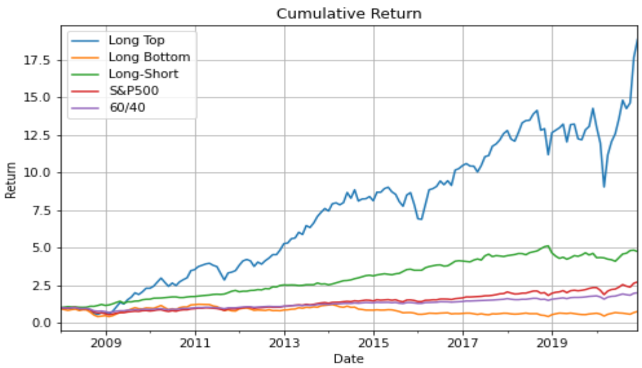
Table 2 - Strategy Returns

Size (ME) breakpoint Median Market Equity (ME)		**Book-to-Market (BE/ME) breakpoints**
Small Value	**Big Value (Losers are kept)**	90%
Small Neutral	Big Neutral	
Small Growth (Winners are sold short)	Big Growth	10%
*Long/Short = 1/2 * Big Value (losers) – 1/2 * Small Growth (winners)*		

3. Performance Overview

The long side of the strategy performs fairly well the entire sample period, with an average annual return of roughly 27.33%. Conversely, the short side of the strategy, as a standalone long investment

Figure 1 - Cumulative Performance Comparison



strategy, offered an average annual return of 2.4%. The benchmark portfolios, the SPDR S&P500 ETF Trust (SPY) and a 60/40 portfolio - weighted 60% in the S&P500 (SPY) and 40% in Vanguard's Total Bond Market ETF (BND) -, offer average annual returns of 11.04% and 5.79%, respectively. The Long-Short portfolio offers a higher average annual return of 12.47% relative to the S&P500 benchmark portfolio while entailing a lower level of volatility of around 9.54% (versus 15.80%). The benchmark 60/40 portfolio implies a similar level of volatility relative to the Long-Short portfolio (9.71%) but falls shorter on annual returns. In other words, the Long-Short portfolio offers a greater reward (excess return) per additional unit of risk, with a Sharpe Ratio of 1.31 (versus the S&P's 0.66 and the 60/40's 0.79). The Long-Short portfolio comfortably (cumulatively) outperforms both the S&P500 and 60/40 benchmark portfolios throughout the entire sample period (with return spreads widening substantially from the aftermath of the financial crisis onwards). Please find a summary of performance metrics in the table below (long and short portfolios are henceforth designated 'Top' and 'Bottom', respectively):

Table 3 - Summary of Performance Statistics[3]

	Long Top	**Long Bottom**	**Long-Short**	**S&P500**	**60/40**
Annualized Return (%)	27.33%	2.40%	12.47%	11.04%	5.79%
Annualized Volatility (%)	30.65%	30.48%	9.54%	15.80%	9.71%
Sharpe Ratio	0.8736	0.0605	1.3065	0.6636	0.7925
Skewness	0.4684	0.2490	-0.5378	-0.6461	-0.6892
Kurtosis	3.1975	1.6049	1.8784	1.4739	2.2812
Positive Months (%)	66.67%	48.08%	71.15%	64.74%	62.18%
Cumulative Return (%)	1884.96%	75.02%	473.06%	271.31%	199.26%
Max. Drawdown (%)	45.27%	66.68%	20.07%	47.31%	31.23%

In line with the relative-distress factor theory, companies with high book-to-market ratios (more heavily discounted/ distressed firms), are intrinsically riskier, and should therefore offer higher expected returns. Conversely, companies with low book-to-market

[3] Contents of Table 3 reflect the gross (total; not in excess of the risk-free rate) performance of the strategy (no transaction costs considered) for the entire sample period.

ratios, perceived as safer, should offer lower expected returns. This rationale is behind the choice of losers and winners: losers with high book-to-market ratios should consistently win over the course of time, and winners with low book-to-market ratios should experience persistent losses. This is indeed the case: albeit not the optimal choice on a risk-adjusted basis, the 'Top' portfolio eclipses those of all other alternative strategies concerned in terms of cumulative performance. Liquidity shocks, or mismatches between supply and demand of certain stocks within this cohort, can be partially to blame for the losses they experience more seldomly than not. On the other hand, the 'Bottom' portfolio, comprised of stocks of firms with low book-to-market equity, performs poorly throughout the entire sample period. Investor overreaction (optimism), or the previously mentioned cognitive errors, as the driver of recent gains, fades away when these very same investors start discounting from stock prices the fundamentally poor earnings prospects of such stocks; it might be the case that investors take their time to adjust to new information. While the Covid-19 pandemic dented the performance of the market as a whole, *big value* stocks on the long side and *small growth* stocks on the short side cushioned the strategy against the market turbulence felt during the 2008 financial crisis.

Finally, 3- and 5-factor Fama and French regression analysis attest to the significance of both HML and SMB factors in explaining the returns of the Long-Short strategy. The former responds positively, and the latter responds negatively, as expected. Interestingly, the market coefficient is insignificant in all regressions. The R^2, that gauges the explanatory power of the model, is unquestionably low, which begs the question of which other factors can be driving the returns of the Long-Short strategy. The following table presents a summary of the conducted regression analysis for (1) the entire sample period and for (2) the first and (3) second halves of the sample period:

Table 4 - Regression Results[4]

CAPM	Full Sample	1st Half of Sample	2nd Half of Sample
Alpha	0.0098 (0.000)	0.0125 (0.000)	0.0073 (0.016)
Mkt-Rf	0.0642 (0.165)	0.1037 (0.110)	0.0283 (0.673)
Adj. R-Squared	0.006	0.022	-0.010
FF3			
Alpha	0.0117 (0.000)	0.0138 (0.000)	0.0089 (0.002)
Mkt-Rf	0.0484 (0.310)	0.0413 (0.571)	0.0593 (0.373)
SMB	-0.2587 (0.005)	-0.1829 (0.267)	-0.3190 (0.005)
HML	0.3461 (0.000)	0.3827 (0.002)	0.3081 (0.001)
Adj. R-Squared	0.153	0.135	0.152
FF5			
Alpha	0.0107 (0.000)	0.0116 (0.001)	0.0087 (0.003)
Mkt-Rf	0.0725 (0.144)	0.1192 (0.127)	0.0540 (0.460)
SMB	-0.2153 (0.020)	-0.1637 (0.294)	-0.2759 (0.029)
HML	0.3870 (0.000)	0.4829 (0.001)	0.3405 (0.004)
RMW	0.3197 (0.016)	0.5566 (0.008)	0.1979 (0.314)
CMA	0.0083 (0.959)	-0.0446 (0.860)	-0.0010 (0.996)
Adj. R-Squared	0.179	0.199	0.152

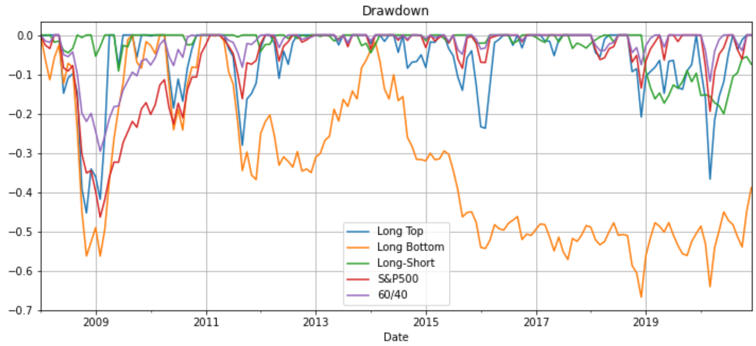
Correlation matters in particular to investors who are invested in assets other than my proposed strategy. A desirable characteristic of a portfolio comprised of multiple assets is low correlation between such assets, as a low correlation minimizes the risk (volatility) of the portfolio; the lower the correlations between assets, the lower the magnitude of drawdowns (at the expense of some forgone returns, especially if correlations are negative). The following table attests to the very low correlation between the long-short strategy and the considered benchmarks:

Table 5 - Correlation Matrix

	Long-Short	S&P500	60/40
Long-Short	1.0000	0.1283	0.1160
S&P500	0.1283	1.0000	0.9900
60/40	0.1160	0.9900	1.0000

[4] Table 4 shows CAPM, FF3M, and FF5M regression results for the factor models against the absolute returns of the long-short strategy without transaction costs for the full sample period and 1st and 2nd halves of the sample period. The p-value is in parentheses in front of the coefficient of each factor. All values presented are monthly (including the Alpha).

Figure 2 - Maximum Drawdowns



Because the strategy entails a fairly large number of transactions on a monthly basis, some of which on small, often illiquid stocks, one cannot turn a blind eye to the transaction costs. To this extent and considering previous research on the topic (see appendix 1), I considered 10 basis points for transactions on the long side and 15 basis points per transactions on the short side. While these costs depress the cumulative performance of the long-short strategy, it still cumulatively, and on a risk-adjusted basis, outperforms the considered benchmarks[5]. Please find a graphical representation of the cumulative (gross and net) performance of the long-short strategy relative to benchmarks below:

Figure 3 - Net Cumulative Performance Comparison

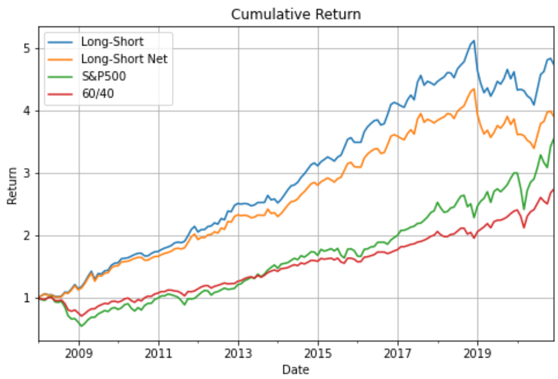


Table 6 - Summary of Performance Statistics (Net vs Gross)

	Long-Short	Long-Short Net
Annualized Return (%)	12.47%	10.97%
Annualized Volatility (%)	9.54%	9.54%
Sharpe Ratio	1.307	1.149
Skewness	-0.538	-0.538
Kurtosis	1.878	1.878
Positive Months (%)	71.15%	67.31%
Cumulative Return (%)	473.06%	389.93%

[5] Both benchmarks are comprised of Exchange Traded Funds (ETFs), which do not usually entail transaction costs for the investor (given the competition between ETF providers, transaction costs have been steadily falling over time. This is consistent with the fact that big ETF providers, like BlackRock or Vanguard, have been driving smaller ETF providers out of business).

4. Methodology

Stock return data is retrieved from CRSP for the US and from Compustat for all other countries, with all accounting data (namely the constituents for book equity calculation, as well as fiscal dates) also coming from Compustat, in US dollars. Please note that this data, including pre-calculated variables, was sourced from the paper *'Is there a Replication Crisis in Finance?'* (Jensen, Kelly and Pedersen 2021), which served as the building block for the final project of the *Data Analytics for Finance* course, lectured at Nova School of Business and Economics by Professor Nicholas H. Hirschey. The choice of this particular dataset reflected, to a big extent, the difficulty in accurately merging CRSP and Compustat data together, as each database has its own unique stock (and company) level identifiers. While merging both databases via CUSIP (an 8 or 9-digit unique stock identifier operated and maintained by the *S&P Global Market Intelligence* that spans both CRSP and Compustat) would have been possible, it would not have been as accurate (see appendix 2).

Delisting returns are separately sourced, per PERMNO, from CRSP via the Wharton Research Data Services (WRDS), cleaned (to ensure non-numerical/ invalid records are filtered out) and subsequently merged on PERMNO and date[6] with the main CRSP data frame. The data frame containing the delisting returns is then merged on GVKEY and (observation/ calendar) year with the merged CRSP/ Compustat data frame. In line with Fama and French's portfolio formation framework, yearly accounting/ fundamental variables are forward filled at the beginning of every calendar year (i.e., accounting/ fundamental variables are held constant throughout the year).

Once all relevant CRSP and Compustat information has been merged together, book equity entries are lagged by one (fiscal) year throughout the sample period, in line with Fama and French's portfolio formation framework. The same is done with market equity entries,

[6] *Month-end dates are considered (e.g., March 31st, 2002).*

allowing for the construction of the book-to-market ratio (BE/ME) at year t, which is equal to the lagged book equity (book equity at year t-1) divided by the lagged market equity (market equity at year t-1). The time gap between returns and accounting/ fundamental data rests on a conservative approach to the way the market incorporates new information; novel accounting/ fundamental data may not be available at the time portfolios are formed.

Portfolio construction (and subsequent rebalancing) is done every June, and entails calculating the book-to-market (BE/ME) and size (ME) breakpoints. To this extent, every June month-end, a portfolio comprised only of New York Stock Exchange (NYSE) common stock with available relevant data in the preceding calendar year is formed. This portfolio is deemed the June portfolio. To every stock (GVKEY) in the June portfolio, the market equity in December of the preceding calendar year (year t-1) is matched. The lagged book equity (year t-1) is then divided by the lagged December market equity (year t-1), yielding book-to-market (BE/ME) ratios. The book-to-market breakpoints used in my strategy correspond to the 90^{th} and 10^{th} book-to-market percentiles. The median market equity (ME) in June portfolio serves as the size breakpoint.

After obtaining the uppermost and bottommost book-to-market portfolios (above the 90^{th} and below the 10^{th} percentiles, respectively) and splitting them according to size (median market equity), the breakpoints are carried forward, serving as reference points throughout the following year (e.g., from June of year t to June of year t+1). Monthly returns are then lagged by one month for the entire sample, and deciles are assigned respectively (i.e. deciles assigned based on prior-month returns). From the uppermost, big (above median ME) book-to-market portfolio, only losers are selected (deciles 0[7] through 4); from the bottommost, small (below median ME) book-to-market portfolio, only winners are selected (deciles 5 through 9). The long-short strategy consists of holding the losers and selling short the winners.

[7] Python lists are zero-indexed. Accordingly, deciles range from 0 to 9, inclusive.

5. Limitations

As with every investment strategy, there are some factors that can significantly tamper with its performance and/ or question its theoretical foundation. Transactions costs and short-selling constraints are common examples. In the particular case of this strategy, it is also worth considering the findings in The Devil in HML's details (Asness and Frazzini 2013). In this paper, the authors argue that, notwithstanding the reasonable conservativeness of Fama and French's approach in the construction of book-to-market portfolios (using lagged records to calculate book-to-market breakpoints, thereby avoid forward looking biasedness), a superior strategy, that resorts to the most recent, up-to-date records of book value per share and price for the calculation of book-to-market breakpoints, can and should be used. The authors rest their case on the dynamic relationship/ interplay between value and momentum, unknown to financial literature in the 1990s; value stocks, the authors argue, experience intra-year price drops unaccounted for in the standard Fama and French (1992) model.

Survivorship bias should also be considered when implementing my strategy. If the long-short approach rests on indices like the S&P 500 or the Russell 1000, for instance, it is important to keep the losers in the investable universe. As (persistent) losers are gradually replaced by winners in such indices, using the most up-to-date constituents would undermine the performance of the strategy. Moreover, the considered sample period can be somewhat limitative: the performance of the strategy is analysed over a 12-year period (from January 2008 through December 2020); it is totally conceivable that the strategy could perform differently out-of-sample. For instance, in periods of high economic growth, it can be argued that *small growth* companies can perform well, significantly undermining the performance of the long-short strategy.

It is also worth mentioning that a long-short strategy requires a margin account to borrow the stocks to be sold on the short-side, which makes the strategy difficult to implement for retail investors; a sound understanding of the financial markets, willingness to take on a significant level of risk (especially when increasing gross exposure past 100%) and a sizable amount of capital can make the implementation of a long-short strategy prohibitive.

Finally, past returns are not indicative of future returns, and one should therefore interpret the returns of my strategy with caution; the cyclicality of markets, and their ever-changing dynamics, can render my strategy unfruitful in the future.

6. Conclusion

The characteristics of the long-short strategy allowed it to outperform considered benchmarks on a risk-adjusted basis throughout the entire sample period, especially during times of economic distress. Notwithstanding a sizable degree of exposure to the US market, the returns of the long-short strategy showed little correlation with those of considered (US-focused) benchmarks, helping to lower the overall volatility of the portfolio and protecting the investor against uncomfortably high drawdowns. In particular, *big value*, operationally-efficient stocks, with a solid foothold in the market (especially in the debt market) withstood the aftermath of the financial crisis. On the other hand, *small growth*, often inefficient, poorly-managed companies had a hard time navigating low investor confidence.

However, the analysis the performance of the strategy during the proposed sample period is not as indicative of future performance, nor it reflects how the strategy would have perform out-of-sample. For instance, pricing of stocks based on fundamental data is becoming increasingly questionable: over the last few years, stocks deemed traditionally overpriced in light of their fundamentals have been the major profit drivers on the stock market. The investor should therefore regularly monitor the performance of the strategy in the future in order to modify it, if necessary. Notwithstanding these and other limitations, I am confident that my analysis is solid, theoretically sound, and implementable.

I. Table of figures

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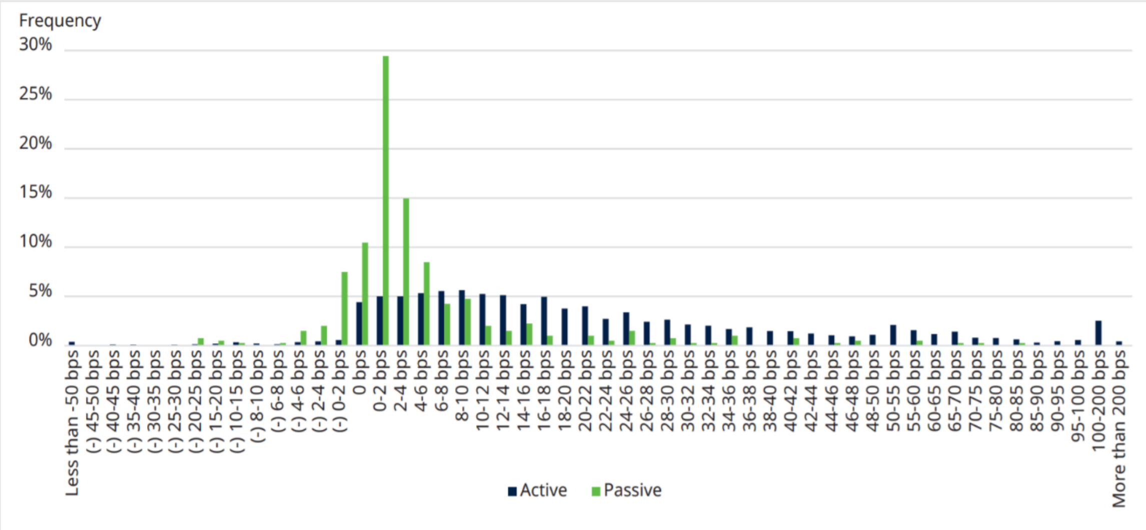
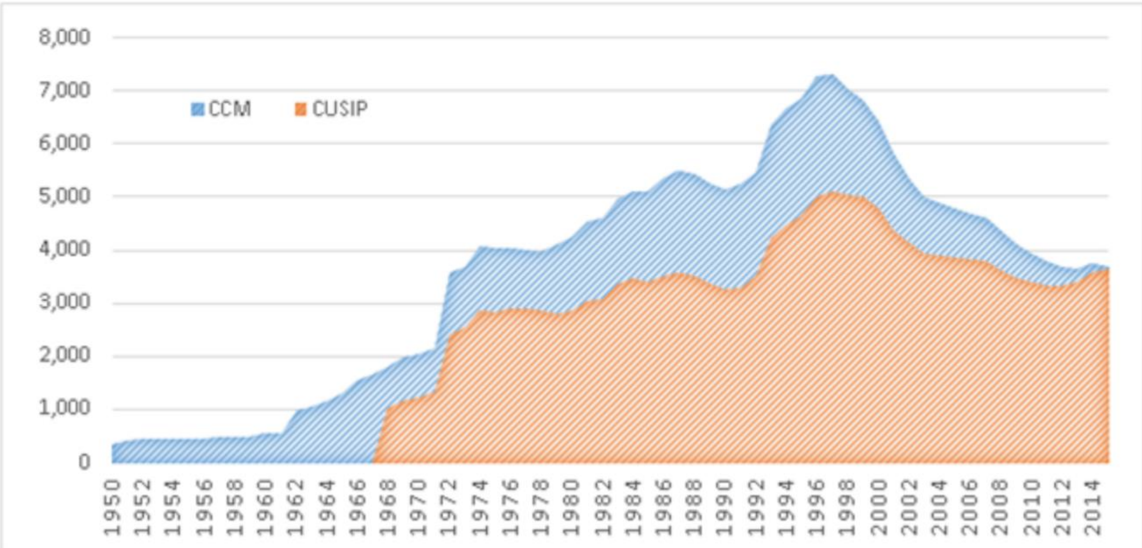
III. Appendices

1. Distribution of transaction costs across active and passive equity funds



The majority (in terms of frequency) of transactions costs (which include implicit and explicit components) sit within the 0-2 basis points (bps) range for passive funds. Passive funds usually incur in transaction costs whenever they adjust asset weights in line with pre-defined criteria (that underlies their tactical asset allocation). Passive funds are therefore the reference for the long-short-strategy regarding transaction costs. Source: *The Transaction Costs Manual*, Schoders 2021.

2. Merged CRSP/ Compustat database (CCM) vs. CUSIP-matched CRSP and Compustat companies



The merged CRSP/ Compustat (CCM) database more accurately matches records between the two data providers, thus increasing the investable universe. Merging by CUSIP, on the other hand, would have excluded a sizable number of companies. Source: Wharton Research Data Services (WRDS).

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ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

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Title

Analysis Of Quantitative Investment Strategies

Abstract

The group report aims to combine the five individual strategies, covering equities and commodities. Motivated by the Markowitz optimization (1952), we combine the strategies by optimizing the risk-adjusted return (Sharpe Ratio), resulting in an optimized group portfolio. In our backtesting period from April 2010 to December 2020, the group strategy yields on average 8.48% yearly. After adjusting the returns for transactions costs, the strategy yields 6.94%. Our strategy underperforms the S&P 500 that yields on average 11.33% each year. On the risk-adjusted basis, the optimized strategy outperforms the market with a Sharpe Ratio of 1.76 compared to 0.80.

Keywords

Finance; Financial Markets; Data Analysis; Portfolio Optimization

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1. Introduction

Stock markets are an excellent platform for companies to raise capital and investors who want to deploy risk capital in return for reward. In the pursuit of enhancing their own wealth, stock market participants attempt to beat the market by exploiting market inefficiencies, gaining superior insights, or developing their own investment strategies. The inevitable competition leads to a market where uncovering data unknown to other analysts becomes difficult. This is also the premise of the Efficient Market Hypothesis (EMH) by Eugene Fama (Fama 1970) which assumes an efficient market whose prices reflect all available information. Consequently, realizing abnormal returns consistently should not be possible in such a market.

The aim of this analysis is to construct a portfolio which provides investors superior risk adjusted returns above the market. We will address the recently increasing appetite for alternative assets and construct a portfolio of four equity and one commodity strategy. Each strategy systematically follows economically justified factors to provide attractive returns on a risk-adjusted basis. We combine the individual strategies in line with the Markowitz optimization (1952) by maximizing the Sharpe Ratio. Moreover, we backtest the resulting strategy using an in-sample and out-of-sample period to test the consistency of the strategy's performance. In the whole sample period, the group strategy underperforms the S&P 500 in terms of total return. However, when adjusting for risk, the strategy outperformance the S&P 500 with Sharpe Ratio twice as big.

The remainder of the report is organized as follows. Section 2 briefly describes and analyses the individual strategies. Section 3 describes the methodology and the portfolio optimization process. Section 4 examines the performance of the optimized group strategy during the in-sample and out-of-sample period. Section 5 presents the regression analysis using CAPM, FF3 and FF5 and Section 6 addresses implementation issues. Finally, Section 7 concludes.

2. Individual Strategies

2.1 Commodity Strategy (Strategy 1: CMD)

2.1.1 Economic Motivation

Commodities come with a set of positive properties which is why it became such an increasingly popular asset class. Most investors use commodities as a portfolio diversifier, equity risk hedge or inflation hedge. Moreover, trading commodity futures requires less capital given its leverage, which increases the net performance. However, simply investing in commodities or commodity indices unfortunately does not provide good returns historically. Appendix 2 shows the cross-section returns of the 24 Goldman Sachs Commodity Index (GSCI) constituents and portrays a clearly heterogenous picture. Some commodities such as sugar and soybeans are constant winners with average annual returns of around 10% while natural gas loses 20% per year on average. This is not surprising since commodities are quite different by nature and livestock for instance is affected by different factors than metals or energy commodities. Hence, the question arises how to keep the benefits of commodity investments but get rid of the bad performance.

The first step to approach this question is to expand the investable universe. The commodity futures market can be compared to an insurance mechanism where hedgers and speculators agree on a price for the transfer of risk. For example, if a risk averse oil company wants to hedge their product, they could sell a futures contract and lock in the price. However, the futures price should be below the expected spot market price to entice the speculator to buy. As maturity approaches, the futures price and spot price converge and the initial spread is the risk premium earned by the speculator, and price (insurance) paid by the hedger. The same concept applies to consumers who want to hedge their consumption. If a risk averse consumer wants to hedge its commodity demand, one could lock in the price today by buying a commodity future. However, the price should be above the expected spot price so that the speculator will earn the risk premium as the futures price declines and converges to the spot price. For further information regarding the composition of the commodity futures risk premium please see chapter 1.2 from the individual strategy report. The main takeaway here is that investors can earn the risk premium not only by being long commodities but also by being short.

Consequently, commodity investing should be approached with a long-short strategy in order to increase returns by being long trending assets (e.g., sugar, soybean) and short underperforming assets (e.g., natural gas), however, maintain the positive diversification effect.

2.1.2 Strategy

The investment strategy is a long-short portfolio of the most backwardated and contangoed commodities. The roll-yield which is the slope of a distant futures contract, and the front month futures contract serves as the signal for backwardation/contango markets. Next, the futures contracts will be ranked by the roll-yield and top/bottom 30% portfolios will be constructed and rebalanced weekly. The top 30% highest roll-yield commodities (backwardation) will be used to construct the long portfolio and vice versa.

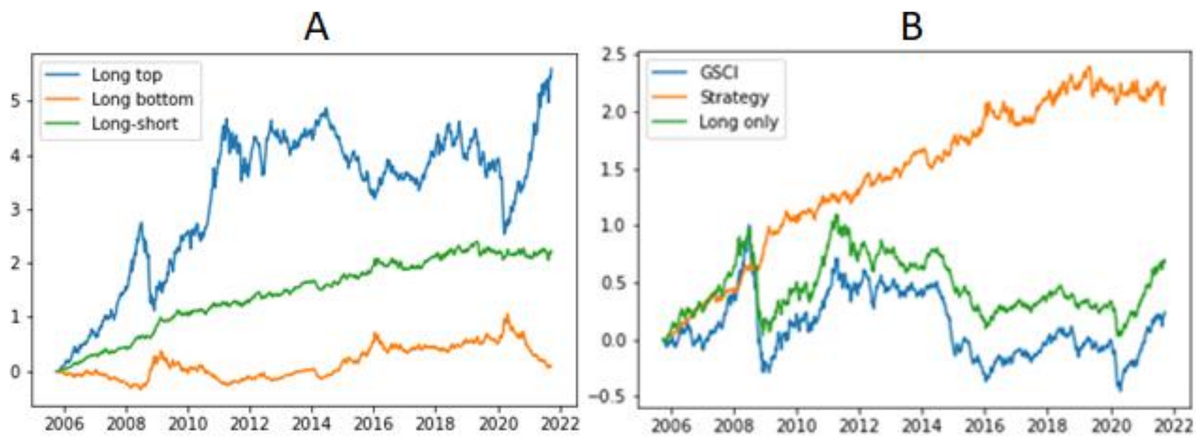
In contrast to other studies (e.g., Basu and Miffre 2013, Erb and Harvey 2006), the portfolios will not be constructed by using the front or second month contracts but distant contracts. The distant contract is usually the 8th contract for the energy/metals sector and 4th for agriculture/livestock sector (see appendix 2 of individual report). The idea is that distant future contracts are less volatile as supply and demand shocks affect rather the front end of the curve in the short term. As maturity is longer for distant contracts, the market can digest recent news more smoothly. Hence, we would expect the distant contracts to offer higher Sharpe Ratios. Moreover, rebalancing occurs weekly instead of the widely used monthly approach. Finally, consistent with other studies on this topic, the investments will be made on a fully collateralized basis. This will simplify the investment process, return calculation, and provide the most conservative outcome.

Furthermore, academic literature talks about the financialization of the commodity market from approximately 2004 onwards (Zaremba 2016). This term refers to the fact that the commodity market only became mainstream in the 21st century. The trading volume experienced exponential growth and the amount of non-professional market participants also increased drastically. More details can be found in the individual report; however, the rationale is that the increasing interest in the commodity inherently increases liquidity provides a good argument to explore the less liquid distant future contracts.

2.1.3 Performance Overview

As the sample consisted of the 24 GSCI constituents, the GSCI will also serve as the performance benchmark as well as an equal weight long only portfolio of the GSCI constituents. Figure 1B presents the cumulative gross performance of the strategy compared to the benchmarks. The GSCI only returned 24% over the period from 2005 to 2021 with an average annual return of 4% and a Sharpe Ratio of 0.18. The equal weight GSCI performed slightly better than the GSCI because the metals sector in particular performed extraordinarily well but is underweight in the GSCI.

Figure 1- Commodity strategy vs. Benchmark



In contrast, the long-short portfolio provides a total return of 221% with a Sharpe Ratio of 1.05. That results in an average annual return of 7.58% which could be categorized as an equity like return. Looking at the 30% top/bottom portfolios as standalone strategies one can conclude that the long backwardation commodities contributed the vast majority of the performance with over 500% cumulative return over the period between 2006-2022 (figure 1A). The short contango portfolio resulted approx. break-even but its negative correlation to the long-backwardation portfolio provides valuable diversification, hence the long-short portfolio does not experience noticeable drawdowns and results in a Sharpe Ratio of 1.05.

However, this performance should be controlled for transaction costs as weekly rebalancing results in many trades and illiquid assets are prone to incur higher transaction costs.

Table 1 – Summary of performance statistics (with transaction costs)

Transaction Costs	**0.00%**	**0.03%**	**0.06%**	**0.09%**	**0.12%**	**0.15%**	**0.20%**
Total Return	221.8%	206.5%	191.9%	178.0%	164.8%	152.2%	132.5%
Average Return	7.58%	7.28%	6.97%	6.67%	6.36%	6.05%	5.55%
STDEV	7.24%	7.24%	7.25%	7.25%	7.25%	7.25%	7.26%
Sharpe Ratio	1.05	1.00	0.96	0.92	0.88	0.83	0.76
Excess kurtosis	0.81	0.81	0.81	0.82	0.82	0.82	0.82
Skew	-0.15	-0.15	-0.15	-0.15	-0.15	-0.15	-0.15
Best week	3.34%	3.34%	3.34%	3.33%	3.33%	3.33%	3.32%
Worst week	-3.77%	-3.78%	-3.78%	-3.78%	-3.79%	-3.79%	-3.80%
Positive Weeks	56.59%	56.35%	56.12%	55.76%	55.64%	55.40%	55.04%

Table 1 exhibits several performance statistics of the commodity futures strategy controlled for a set of transactions costs up to 0.2% per trade.

Table 1 presents the performance statistics for a set of different reasonable transaction costs. Even the assumption of 0.2% transaction costs per trade results in a Sharpe Ratio of 0.76 and a total return of 132% over 15 years. Hence, the outperformance of the GSCI and long only alternative is evident even with conservative transaction costs.

When excluding the most illiquid contracts that did not trade at least USD 75 million dollars during the last four weeks on average, the results look as presented in Table 2 (more in-depth volume analysis can be found in the individual report appendix). The gross strategy

Sharpe Ratio falls from 1.05 to 0.87. Overall, even without the most illiquid contracts and conservative transaction costs up to 0.2% per trade, the strategy achieves a Sharpe Ratio of 0.59 which is substantially better than the GSCI (0.18).

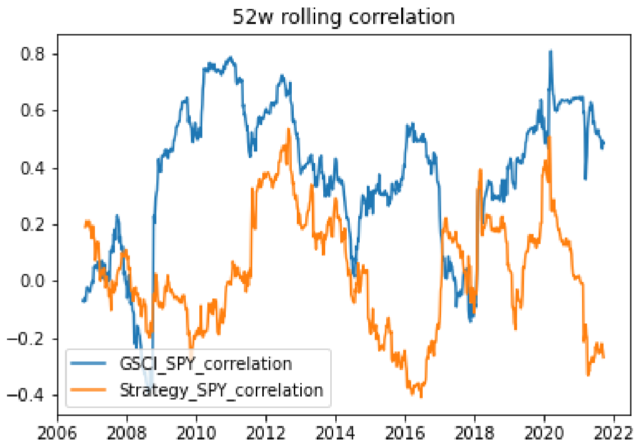
Table 2 - Commodity strategy without the most illiquid contracts

Fees	0.00%	0.03%	0.06%	0.09%	0.12%	0.15%	0.20%
Total Return	176.8%	162.8%	149.6%	137.0%	125.0%	113.7%	96.0%
Avg Return	6.67%	6.34%	6.02%	5.69%	5.37%	5.05%	4.51%
STDEV	7.66%	7.66%	7.67%	7.67%	7.67%	7.67%	7.67%
Sharpe Ratio	0.87	0.83	0.79	0.74	0.70	0.66	0.59
Excess kurtosis	1.56	1.57	1.57	1.57	1.57	1.57	1.58
Skew	0.06	0.06	0.06	0.06	0.06	0.05	0.05
Best week	5.40%	5.39%	5.39%	5.39%	5.39%	5.39%	5.38%
Worst week	-3.77%	-3.78%	-3.78%	-3.78%	-3.79%	-3.79%	-3.80%
Positive Weeks	56.00%	56.00%	55.64%	55.52%	55.28%	54.92%	54.68%

Table 2 presents several performance statistics of the commodity futures strategy without contracts which traded below $75 million USD per week on average during the last four weeks.

Therefore, investors who want to diversify their portfolio with alternative assets should consider whether a long only approach in commodities is the most optimal asset allocation method. It should be noted, however, that a long-short portfolio does not provide the inflation hedge which commodities naturally provide. Hence, the increased return from a long-short portfolio should be seen as compensation for the lost inflation hedge. In our analysis, the increased performance comfortably compensates for this. In addition, the long-short portfolio serves as a better equity risk hedge. Figure 2 presents the one year rolling correlation coefficient between the GSCI and the S&P 500 index as well as the strategy and the S&P 500 index. The former has an average of 0.37 and the latter 0.02, which indicates that the long-short portfolio is in fact a quite good hedge to the U.S. equity market. In particular, periods around 2010 and 2020 which can be characterized by volatile markets show an widening spread in figure 2, which supports the thesis of the strategy being a good equity hedge.

Figure 2 - Commodity strategy as an equity hedge



To sum up, this long-short commodity futures strategy provides equity like returns and serves as a better equity risk diversifier than the widely known GSCI index even when taking reasonable transaction costs and illiquidity into consideration.

2.2 Short-Sale Constrained Stocks Strategy (Strategy 2: SCS)

2.2.1 Economic Motivation

In the past months, short selling has attracted more attention in the finance industry and media. One of the main reasons for investors to short a stock is when they expect that the stock price will decrease in the future. To do so, they borrow the stock from a broker and sell it on the market for its current price. Another reason to short sell a stock is when the investor wants to hedge an open long position of the stock he is about to short. Later, the investor has to give back the borrowed stock resulting in two possible outcomes: (1) the stock price has increased, meaning that the investor has to buy back the stock at a higher price which results in a loss, or (2) the price of the stock has decreased, meaning that the investor buys back the stock for a lower price, gives it back, and makes a profit.

A stock is considered constrained when an investor cannot borrow the stock due to a lack of supply (for example, when a stock has low institutional ownership wherefore there are not many stocks on the market that can be borrowed). Another reason for short-sale constraints might be when a stock has an extremely high demand for borrowing. The paper of Asquith et al. (2005) found that short-constrained stocks underperform the market in the period from 1988-2002 on a monthly basis by 2.15%. Asquith et al. (2005) used the short interest ratio as a proxy for the demand and institutional ownership as a proxy of the supply of the stock. They consider a stock as short sale constrained when it fulfills two conditions: (1) the stock must be in the highest percentile of the short interest ratio, and (2) the stock is included in the lowest third of the institutional ownership. Moreover, they find that constrained stocks significantly underperform when the portfolio is equally weighted relative to a value-weighted portfolio.

2.2.2 Strategy

The implemented strategy is based on the assumptions of the Asquith et al. (2005) paper that the short interest ratio is a proxy for the demand of a stock and that the institutional ownership is a proxy for the supply of the stock. Since the dataset used to backtest the strategy contains fewer stocks than the one from Asquith et al. (2005), I consider a stock as short sale constrained when it meets two conditions: (1) the stock is included in the highest decile of short interest ratio and (2) the stock is in the lowest third of institutional ownership. The strategy goes long on stocks that are least likely to be affected by short sale constraints (stock in the lowest decile of short interest ratio and the highest third of institutional ownership) and short on constrained stocks as defined above. Moreover, the long and short portfolios are equally weighted, which is in line with the previously mentioned findings of Asquith et al. (2005). The portfolio is rebalanced at the beginning of each month. To construct the signal, first, the stocks belonging in the long and short portfolio based on the short interest ratio and institutional ownership in month t-1 are determined. Then, using that signal, the returns of the strategy based on the monthly returns for month t are calculated. Since the strategy is rebalanced at the beginning of each month, the data for the short interest ratio and the institutional ownership are retrieved monthly. Moreover, the monthly returns are calculated based on daily returns by calculating the compounded monthly returns for each stock. The strategy is performed using 952 companies from the Russell 1000 as of the beginning of 2010 in order to avoid survivorship bias. For more details, refer to the individual report of "Short interest ratio and institutional ownership: Quantitative investment strategy with short-sale constrained stocks".

2.2.3 Performance Analysis

This section gives a quick overview of the performance analysis of the sub-strategy as defined above. In order to measure the performance from different perspectives, standard measures are being used, such as the Average Return and Standard Deviation. Furthermore, the Sharpe Ratio and Information Ratio are calculated to obtain risk-adjusted results. The CAPM and Fama-French Three Factor Model are used to determine the required rate of return based on the exposure to certain factors and give us information on to what degree the strategy is exposed to a certain risk. Table 3 presents the results for the full sample period (in-sample) and the first and second half (out-of-sample) to test the consistency of the strategy in different periods. The yearly Average Return in the whole sample period is 8.60%, which is mainly based on the high returns in the first sample half (12.75%). However, the second half of the sample (4.45%) performs quite poorly compared to the other half. The Standard Deviation measures the strategy's risk in a certain period. The second half (15.60%) has the highest standard deviation, and the first sample (10.46%) the lowest, resulting in a volatility of 13.29% for the whole sample. The Sharpe Ratio incorporates, besides the returns of the strategy also the risk. In line with the previous results, the first half of the sample (1.219) performs best on a risk-adjusted basis and the second half the worst (0.285), leading to an overall Sharpe Ratio in the entire sample period of 0.647.

The performance analysis using the CAPM, and Fama-French Three Factor Model suggests that the strategy has low and often insignificant exposure to most factors. Consistent with the other performance measures, the first half performs best and the second half worst. For more details, refer to the individual report of “Short interest ratio and institutional ownership: Quantitative investment strategy with short-sale constrained stocks”. The Information Ratio is calculated using two different approaches: (1) several major market indexes serve as a benchmark, and (2) the ratio is calculated by dividing the corresponding alpha obtained from the CAPM or Fama-French by the standard deviation of the residuals. The Information Ratios using the market index suggest negative ratios for the whole sample period and the second half. It is important to mention that the strategy has a low exposure to the market, wherefore, the market index is not a good benchmark. The results of the Information Ratio using CAPM, and Fama-French indicate that the first half does best and the second half worst. To sum up, the strategy performs well in the first half of the sample and quite poorly in the second. Therefore, it cannot be assumed that the strategy consistently out- or underperforms the market.

Table 3 - Summary of performance statistics (II)

	Full Sample	**First Half Sample**	**Second Half Sample**
Average Return	0.0860	0.1275	0.0445
Standard Deviation	0.1329	0.1046	0.1560
Sharpe Ratio	0.647	1.219	0.285
CAPM	**Full Sample**	**First Half Sample**	**Second Half Sample**
Alpha	0.0660 (0.113)	0.1116 (0.017)	0.0192 (0.785)
Mkt - RF	0.142 (0.073)	0.130 (0.180)	0.157 (0.200)
N	132	66	66
R-Squared	0.025	0.028	0.026
FF3	**Full Sample**	**First Half Sample**	**Second Half Sample**
Alpha	0.0516 (0.211)	0.0972 (0.039)	0.0084 (0.901)
Mkt - RF	0.224 (0.010)	0.169 (0.114)	0.268 (0.044)
SMB	-0.269 (0.066)	-0.015 (0.937)	-0.445 (0.047)
HML	-0.143 (0.239)	-0.344 (0.080)	-0.066 (0.689)
N	132	66	66
R-Squared	0.064	0.075	0.094
IR	**Full Sample**	**First Half Sample**	**Second Half Sample**
IR S&P 500	-0.201	0.188	-0.509
IR Russell 1000	-0.213	0.173	-0.515
IR Russell 3000	-0.210	0.171	-0.507
IR CAPM	0.502	1.085	0.123
IR FF3	0.405	0.970	0.058

Table 3 shows the results of several performance measures for the strategy using the short interest ratio and institutional ownership to determine short sale constrained stocks. The performance of the strategy is calculated using the full sample (in-sample) and the first and second half (out-of-sample). The Average Return, Standard Deviation, Sharpe Ratio, Alpha and the Information Ratios are annualized. The corresponding p-value is indicated in the parentheses.

2.3 Long-Only Value Investing Strategy (Strategy 3: LVS)

2.3.1 Economic Motivation

Benjamin Graham is seen as “the father of value investing" since he is one of the authors of one of the most famous books about the topic - Security Analysis (1934) (Graham et al. 1934). In this book, he made a clear separation between investment and speculation, arguing that investors should analyze the financial statements of companies before investing, and only then buy stocks at a discounted price relative to their intrinsic value. Warren Buffett, one of the most successful value investors in the past decades and one of the richest persons in the world, was his student at Columbia Business School. Graham is also the author of The Intelligent Investor (1949) (Graham 1949), the “bible” of the stock market, where he instructs value investors to create long-term investment strategies and avoid errors.

The logic behind value investing is to buy stocks that are trading at discount relative to their intrinsic value, keep them for the long term, and then sell after the price reaches its intrinsic value. Conversely, the value investor should avoid or short sell the stocks considered overvalued relative to their intrinsic values. Stating that value investors can profit from the mispricing of the stocks is seen as a rejection of the EMH (Fama 1970) that says that all information available is reflected in prices, and so it is impossible to consistently "beat the market" because prices only change with new information.

2.3.2 Strategy

The strategy is built upon the assumption that there are mispriced stocks relative to their fundamental values presented in the financial statements of the companies but that in the long run they will tend to their true intrinsic value. It was analyzed using monthly data only from S&P500 companies from January 2000 until October 2021 (Full Sample). To compare the performance of the strategy in different periods, this sample was divided into Sample 1 (January 2000 – December 2009), Sample 2 (January 2010 – December 2019), and Sample 3 (January

2010 – October 2021). The performance analysis's section will focus on the analysis of this strategy with transaction costs in the Full Sample, Sample 1 ("First Half"), which includes the financial crisis, and Sample 3 ("Second Half"), which includes the effects of the Covid-19 pandemic in the markets. For a more complete analysis of all periods, refer to the individual report about the Long-only Value Investing Strategy.

The strategy is constructed using six indicators that try to identify if a stock is overpriced or underpriced using just fundamental data, and then buy the stock that looks "cheap" relative to its sector peers. As this is a long-only strategy, each indicator is a signal that return 1 (buy-order) if the stock price is "underpriced" according to this indicator, and 0 otherwise. A final signal was then built using these six individual signals that returns 1 (final buy-order) if the stock has at least four individual signals with buy-orders and returns 0 otherwise.

All stocks have the same weight in the strategy. Rebalancing the strategy every month implies costs, so it is assumed that the implementation of the strategy entails a monthly fee of 0.2%. It is important to point out that the returns of the current month (t) are computed using the final signal computed three months prior (t-3) to avoid forward looking bias, i.e., the error of using unknown future information to make decisions in the past, which would lead to erroneous conclusions and unreasonably high returns. To know the reasons behind the choice of the indicators and for a more complete explanation about the signal, refer to the individual report about the Long-only Value Investing Strategy.

2.3.3 Performance Overview

To execute the analysis of this strategy, several performance measures were computed for the different sample periods analyzed, namely the annual average return, the annual standard deviation, the Sharpe Ratio, the total period return, the percentage of positive months, and the maximum drawdown. Also, to understand the excess strategy returns, the Capital Asset Pricing Model (CAPM), the Fama-French Three-Factor Model (FF3) (Fama et al. 1992), and the Fama-

French Five-Factor Model (FF5) regressions were performed to compute the alpha and the exposure of the strategy excess returns to the different factors of the models.

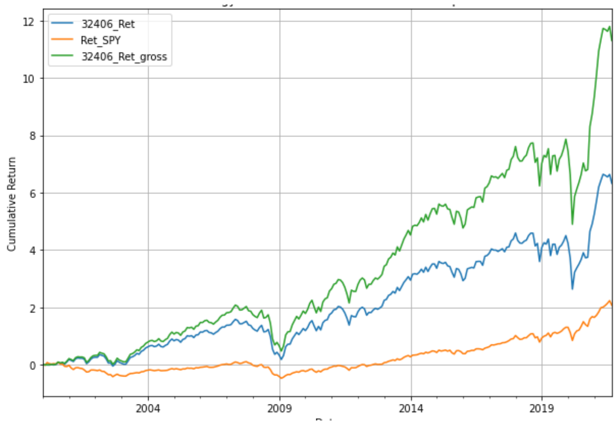
When analyzing this strategy with transaction costs, the full sample had an average annual return of 11.00% with an annual standard deviation of 18.95%. The first and the second half samples also got very similar annual average returns (10.25% and 11.64%, respectively). Regarding the standard deviation, the first half was more volatile (20.17%) than the second half (17.92%). The Sharpe ratio assesses the additional return per unit of risk increased. The second half sample had the highest Sharpe ratio (0.62) and the first half the worst (0.37), resulting in a Sharpe ratio of 0.50 for the full sample, a low value given the volatility of the full sample. The total return for the full sample period was 632%, for the first half sample was 127%, and for the second half was 223%. In roughly 60% (59.77%) of the months in the full sample, this strategy got a positive monthly return. The second half sample got the highest percentage of positive months with 60.99%, while the first half sample had 58.33% of the months with positive returns. The maximum drawdown of the full sample was -54.1%. This was the highest peak decline of the strategy, and it was reached in the first half sample during the financial crisis circa 2008. The highest drawdown of the second half period was -35.02% during the Covid-19 pandemic. These results can be seen in Table 4 below and the cumulative returns of the strategy vs S&P500 for the full sample can be seen in Figure 3.

Table 4 - Summary of Performance Statistics (III)

	Full Sample	**First Half**	**Second Half**
Annual Average Return (%)	11.00%	10.25%	11.64%
Annual Standard Deviation (%)	18.95%	20.17%	17.92%
Sharpe Ratio	0.50	0.37	0.62
Total Period Return (%)	632%	127%	223%
Positive Months (%)	59.77%	58.33%	60.99%
Maximum Drawdown (%)	-54.10%	-54.10%	-35.02%

Table 4 shows the results of some performance measures about the Long-only Value Investing Strategy with transaction costs in the full sample, first half and second half sample periods. The average return, the standard deviation and the Sharpe ratio are annualized.

Figure 3 - Cumulative Returns Strategy vs S&P500 (Full Sample)



Regression analysis shows that the Adjusted R-Squared always increases when factors are added to the regression model. In fact, for the full sample, it increases from 0.842 (CAPM) to 0.912 (FF3) and then to 0.921 (FF5), meaning that the percentage of the excess returns of the strategy explained by the factor model increases the more factors are added to the model. The same is true for both the 1st and the 2nd halves of the sample period. Moreover, the Adjusted R-Squared is always higher in the 2nd half of the sample period than in the 1st half of the sample period in every factor model. For a confidence level of 95%, all alphas - which represent the excess returns not explained by the model - for the full sample and the 1st half of sample period in the FF5 model are not statistically significant, meaning that we fail to reject the null hypothesis. For the same confidence level, the remaining alphas are significant, but all alphas for the second half are negative. Regarding the coefficients of the factors, almost all are significant for a confidence level of 95% in every sample period, except the CMA factor in the FF5 model that it is not significant in the second half sample. The summary of the regression results using the factor models over the excess returns can be seen in Table 5, where the p-value of the coefficients is in parentheses.

To conclude this regression analysis, it is important to refer that the beta of the market risk premium factor is always the highest coefficient in every model and always higher than 1, meaning that the strategy excess returns are more volatile than the market excess returns in every sample period analyzed in this section. A deeper analysis about the performance measures and the regression results is conducted in the individual report about the Long-only Value Investing Strategy.

Table 5 - Regressions Results (III)

CAPM	Full Sample	First Half	Second Half
Alpha (monthly)	0.0014 (0.292)	0.0079 (0.001)	-0.0048 (0.001)
Mkt-Rf	1.1137 (0.000)	1.0962 (0.000)	1.1764 (0.000)
Adj. R-Squared	0.842	0.815	0.897
FF3	**Full Sample**	**First Half**	**Second Half**
Alpha (monthly)	0.0005 (0.625)	0.0041 (0.034)	-0.0029 (0.005)
Mkt-Rf	1.0628 (0.000)	1.0819 (0.000)	1.0753 (0.000)
SMB	0.2605 (0.000)	0.2539 (0.000)	0.2622 (0.000)
HML	0.4080 (0.000)	0.4231 (0.000)	0.3501 (0.000)
Adj. R-Squared	0.912	0.881	0.953
FF5	**Full Sample**	**First Half**	**Second Half**
Alpha (monthly)	-0.0009 (0.350)	0.0021 (0.266)	-0.0033 (0.001)
Mkt-Rf	1.1079 (0.000)	1.1814 (0.000)	1.0677 (0.000)
SMB	0.3288 (0.000)	0.3159 (0.000)	0.3430 (0.000)
HML	0.2287 (0.000)	0.1753 (0.019)	0.2502 (0.000)
RMW	0.1434 (0.002)	0.1761 (0.027)	0.1829 (0.002)
CMA	0.2091 (0.001)	0.2941 (0.004)	0.1038 (0.133)
Adj. R-Squared	0.921	0.893	0.958

Table 5 shows the results of the regressions performed using the factor models over the excess returns of the Long-only Value Investing Strategy with transaction costs in the full sample, first half sample and second half sample. The p-value is in parentheses in front of the coefficient. Alpha presented is monthly.

2.4 Exploring Short Side with a Fundamental Approach (Strategy 4: ESI)

2.4.1 Introduction

Quantifying the impact that short sellers can have in price declines is a really difficult task. These investors are sometimes seen as controversial, as their activity is often blamed for amplifying them. The paper: *'Do short sellers amplify price declines or align stocks with their fundamental values?'* written by Curtis and Fargher (2014) tests up to what extent may short sellers impact price declines and try to respond to one key question: 'Does short sellers take positions in firms with price declines to amplify them, or because they really believe it is overpriced, and wanted to reduce the holding costs for a short position?'.

As a brief introduction, the authors start to distinguish between what they consider the two main different type of short sellers: (1) momentum-based investor – is the one that might have a significant impact by increasing the selling pressure at a given point in time, forcing the stocks to drop below their fundamental values. (2) valuation-based investor- is the investor that shorts a stock based on his strong believes that is overvalued. In this case, authors assume that this kind of investors enhance market efficiency by targeting these overvalued stocks and taking them back to their fair value. Therefore, a value short seller might enhance market efficiency. Afterwards, the authors present two essential conclusions about the topic: (1) after price declines, short investors seem to be concentrated in low fundamental-to-price ratio and that (2) for the most targeted firms by short sellers, returns after price declines are more negative to those overpriced based on their fundamental values. These conclusions will be important to understand some of the concepts presented along the strategy, as they were created based on these two assumptions.

Regarding other paper, Keller et al. (2018) tested how can the traditional cash protection be improved and reduce the overall risk of a given portfolio by allocate their assets based on what the authors called Vigilant Asset Allocation (VAA). It calculates what they named as breadth momentum and whenever breadth is positive the strategy will assume a riskier profile. If in the meantime the breadth momentum decreases, the portfolio will switch its allocation to a less risky approach (i.e., move to cash or low risk bonds). The goal is to improve returns while reducing risk by making more robust allocations according to more or less bullish periods. Though, ESI strategy uses a Modified Asset Allocation (MAA), which is inspired but not equal to VAA. MAA has same intuition but use a different way to calculate its breadth momentum.

In conclusion, ESI strategy will be based on these two papers, however, highly customized for the purpose. The idea is to use their reasoning but do not replicate them.

2.4.2 Strategy

The Portfolio strategy is composed by 4 different components. (1) a long portfolio of 150 stocks; (2) a short portfolio of 150 stocks; (3) ‘IWV’ (iShares Russel 3000 ETF) and (4)

'*IEF*' (iShares 7-10 Year Treasury Bond ETF). To this extent, the strategy is build based on two different parts:(1st) *Modified Asset Allocation* (MAA)- As mentioned before, it will be used to test whether it can improve the risk adjusted return of the portfolio or not by having three different levels of risk profile. By saying that, the portfolio is meant to adjust on a monthly basis, the weights that each one of the four different components has, and this allocation will be made according to the risk level profile defined for each specific month; (2nd) Long & Short stock picking – It relies on the way that long and short portfolio choose different stocks. Based on Curtis et al. (2014) conclusions, it will try to find some heavily shorted and overvalued stock for the short portfolio. On the other hand, it will do the opposite for the long portfolio (by looking for the least shorted stocks and underpriced). To do so, this picking method will use first a short interest filter to signal long and short stocks as a possibility. Afterwards, it uses P/E ratio to sort the ones which seem to be under/overpriced according to its fundamentals. As Curtis et.al (2014) conclude that overpriced firms have higher price declines, it will choose overpriced to short and underpriced to go long.

2.4.3 Signal Construction

2.4.3.1 MAA Construction (two different steps)

- 1st- *ISM PMI breadth momentum*: It is calculated based on PMI monthly output released by ISM. If the output is above or equal to 50, its breadth momentum will be positive, and the opposite if not. The idea is to use it as a leading macroeconomic indicator and include its information in decision making.
- *2nd- SPY breadth momentum*: It is calculated based on SPY S&P500 Trust returns. The equation presented below shows how it is calculated. If its breadth momentum is above or equal to 0, then it will be positive and the opposite if not.

$$SPY\ breadth\ momentum = 12\left(\frac{P_0}{P_{-1}} - 1\right) + 4\left(\frac{P_0}{P_{-3}} - 1\right) + 2\left(\frac{P_0}{P_{-6}} - 1\right) + \left(\frac{P_0}{P_{-12}} - 1\right)$$

In the end, the strategy might have up to three different levels of risk and will adjust its portfolio based on that. If both breadth momentum are positive the strategy will take its ‘riskier’ approach (called Risk-On). In case of both negative it will take the least risky (called Risk-Off). In case of having mixed outputs between them, SPY breadth momentum will work as a tie-breaker (if positive the portfolio will take a third level created for the purpose called Mid-level of Risk, if negative the strategy will take the least risky as if they were both negative). In Table 6, it is possible to see how the strategy allocates their four different components along different risk scenarios.

Table 6 - Modified Asset Allocation

Level of Risk /Assets	Long Portfolio	Short Portfolio	IWV	IEF
Risk-On	1.3	0.3	0.0	0.0
Mid level of Risk	1.0	0.5	0.3	0.2
Risk-Off	0.5	0.5	0.4	0.6

Table 6 shows the asset allocation of ESI Strategy according to MAA monthly risk profile.

2.4.3.2 Long & Short picking

Based on empirical conclusions presented by Curtis et al. (2014), this method will use two different steps to choose its long and short portfolio:

1. Short Interest Filter: Predefine upper and lower limits where those stocks with short interest higher that the upper limit will be selected as possible short stocks and those below the lower limit will be selected as possible long stocks. In the end, this first step will give two different lists of possibilities. One for long and other for short portfolio. The scheme presented below shows how this first step is conducted:

$$Short\ Interest\ filter\!:\ Long \rightarrow [\ 0 : 2\ ]\ \ \&\ Short\ [\ 6 : +inf]$$

2. Price to tracked EPS filter: It will take both lists and look for those with higher ratio value within short possible list and those with lower ratio values in the long possible list. The idea is to target overpriced in the short portfolio in order to increase returns in case of price declines (take profits from Curtis et al (2014) second conclusion), and also

underpriced firms to include in the long portfolio. Each portfolio should equally weight 150 different stocks.

In the end, the stock picking method will be used just for the long and short portfolio construction. Afterwards, they will constitute two of the four different components in the Modified Asset Allocation method. Lastly, MAA will weight them differently according to the monthly breadth momentum explained before.

2.4.4 Performance Analysis

To understand how the portfolio behaved over different time periods, and what might explain such differences, the analysis of the Portfolio is carried out on three different samples: (1) the full period sample, ranging from the beginning of 2003 through the last month of 2020, (2) a first half sample, ranging from early 2003 through mid-2010, and (3) a second half sample, ranging from mid-2010 through the end of 2020. To this extent, the first half sample covers the 2008 financial crisis, and the second half sample covers the Covid-19 crisis. Regarding the Second Half Period, it starts in June 2010 and goes up to the last trading month tested in the sample. The whole idea of splitting the sample in two different ones is to make more concrete conclusions about how differently the strategy behaved along different sample periods. Table 7 below show statistical data regarding these three different periods.

Table 7 - Summary of performance statistics (IV)

	Full Period	First Half Period	Second Half Period
Cumulative Return (%)	1048.4%	545.9%	57.5%
Mean (%)	14.7%	26.3%	5.2%
Volatility (%)	14.6%	15.9%	13.6%
Sharpe Ratio	0.924	1.578	0.294
Skewness	0.168	0,504	-0.597
Kurtosis	2.247	2,306	1.366
Max Drawdown (%)	-33%	-13.1%	-33%

Table 7 shows several statistical measures for the in- and out-of-sample period.

By looking into the table, it seems pretty obvious that there is a huge difference between first and second half strategy performance. Indeed, there is not a single statistic measure that performs better on the second than on the first half. By saying that, it is important to highlight the huge decrease in Sharpe Ratio, indicating that the strategy had a much better risk adjusted return in the first 8 years of the sample. Besides that, the skewness moved from a positive to a negative value in the second half. By doing so, it indicates that returns distribution skewed from right to the left along the whole sample period. Also, and by looking at maximum drawdown value, it was much higher in the second half than in the first. As the maximum drawdown represents the peak to trough decline along a given sample period, 33% would represent a 1/3 loss in the value of whole portfolio. Indeed, this value would be reason to concern any given investor.

To sum up the performance, these differences might be explained by a different number of reasons. Though the one that seems to be stronger is the fact that the strategy clearly looks for some heavily shorted and overpriced firms for the short portfolio (higher probabilities of getting growth stocks) and the least shorted and underpriced firms for the long portfolio (more related with value companies). Moreover, during the past ten years, growth stocks performed much better than value stocks. This might have created a disequilibrium as the portfolio had some heavy losses on shorting some growth stocks and did not make enough returns to compensate them with the long portfolio. Therefore, we strongly believe that this was the main reason for these performance difference along the sample.

2.5 Value, Distress and Short-Term Reversal (Strategy 5: VDS)

2.5.1 Economic motivation

Drawing on the principle of rational (efficient) markets, the Fama-French Three Factor Model (Fama et al. 1992), a significant extension of the Capital Asset Pricing Model (CAPM), sought to explain stock returns by measuring how they responded relative to factors – the High Minus Low (HML) and Small Minus Big (SMB) factors, in particular. To this extent, the authors formed portfolios on size - measured by Market Equity (price times shares outstanding)

- and further broke them down according to Book-to-Market (equity) ratios. The portfolios whose Market Equity sat above the median Market Equity at the end of each June (the portfolio formation month), deemed *big* portfolios, were found to underperform relative to their *small*, below-median counterparts. Simultaneously, portfolios containing stocks with *high* Book-to-Market ratios were found to overperform relative to their counterparts with *low* Book-to-Market ratios. Portfolios on opposite ends of the Book-to-Market spectrum are then combined into a single, long-short strategy: *high* portfolios are held indefinitely, while l*ow* portfolios are sold short.

The explanations – and implications – of these findings have been the source of intense. According to Fama and French, the market judges low stock prices relative to book value as an indicator of poor earnings prospects. The relative distress factor of Chan and Chen (1991) encapsulates this argument well: the authors postulate that marginal firms, whose stock prices have fallen over time because of persistently poor performance, are more likely to shrink in relative size and suffer from high financial leverage (defined as the sum of book value of current liabilities, long term debt, and preferred stock over market value of equity). Should companies continue to perform poorly, shrinking further, and should they fail to change their capital structure accordingly, they will likely suffer from market-imposed financial leverage, as the market keeps discounting its stock price relative to its book value (which widens the gap between book and market equities). Finally, the authors ascribe to the idea that it is not size *per se* that explains the risk-return profile of firms of *big* and *small* firms, but rather characteristics, like cash flow problems or operational inefficiencies, that make them *marginal* and thus more sensitive to changes in the economy. Marginal firms tend to be more concentrated in portfolios comprised of small stocks, which is why the latter are said to be riskier and to offer correspondingly higher returns. This economic rationale, and the interplay between *marginality* and book-to-market, within the Fama and French (1992) portfolio construction framework, is the groundwork upon which my investment strategy is built.

2.5.2 Strategy

As certain stocks appear to behave in a chronically marginal way, I found it interesting to test to what extent a short-term reversal strategy could be compatible with Chan and Chen's findings (within Fama and French's factor construction framework). First proposed by Jegadeesh (1990), a standard short-term reversal is a zero-investment strategy that consists of sorting stocks into deciles based on prior-month returns, buying stocks in the bottom decile (losers) and selling stocks in the top decile (winners). To this extent, a staff report from the Federal Reserve of New York (Da et al. 2011) sought to reconcile two competing, albeit not mutually exclusive explanations of short-term reversal profits:

1. On the one hand, some authors have argued that short-term reversal profits are driven by investor overreaction to information, or cognitive errors, described as the sentiment-based explanation.
2. On the other hand, other authors have described short-term reversal profits as compensation for liquidity providers during periods of larger spreads between supply and demand. This is deemed the liquidity-based explanation.

Da et al. (2011) first decomposed short-term reversal profits into across-industry and within-industry components. As Moskowitz and Grinblatt (1999) pointed out, there is a strong industry momentum, whereby current winner industries outperform current loser industries in subsequent months (this component therefore contributes negatively to short-term reversal profits). The within-industry component therefore remains as the positive contributor: investors overact to firm-specific news but underreact to industry-specific news. Drawing on a modified short-term reversal strategy, the authors effectively reconcile the previously mentioned explanations for short-term reversal profits:

1. The profits from buying losers relate positively and significantly with a lagged aggregate illiquidity measure proposed by Amihud (2002); the higher the level of illiquidity, the larger the profits, which hints at compensation for liquidity provision on the buy-side (buy-side pressure jacks up prices).
2. The profits from selling winners relate positively and significantly with two lagged measures of investor optimism and equity overvaluation - monthly number of IPOs and monthly equity share in new issues (Baker et. al 2006) -, which comprise an aggregate measure of overvaluation (optimistic investor sentiment).

In short, liquidity shocks always seem to drive the reversal on recent losers (long side) while investor sentiment always seems to drive the reversal on recent winners (short side). To this extent, I constructed equal-weighted portfolios based on size and book-to-market ratios according to the original Fama French framework (thereby avoiding forward looking bias[1]), and then proceeded to sort them by their prior-month returns. My strategy ultimately rests on buying loser stocks that sit above the median size (market equity) breakpoint and within the uppermost book-to-market decile (9%), or bracket, and selling winner stocks that sit below the median size (market equity) breakpoint and within the bottommost book-to-market decile (10%), or bracket, within each industry.

Breakpoints for size and book-to-market are calculated every year and carried forward; portfolio construction/ rebalancing is therefore carried out on a yearly basis (e.g., breakpoints calculated in June of year t-1 serve as reference points for the following twelve months). My approach differs from the original Fama/ French approach to the extent that:

[1] "…a type of bias that occurs when a study or simulation relies on data or information that was not yet available or known during the time period being studied." (Via Corporate Finance Institute).

1. The book-to-market breakpoints I used differ from those used by Fama and French (70% and 30%, respectively), more aggressively segregating stocks into value or growth portfolios, aiming to reinforce the validity of my strategy analysis.
2. The long side of the portfolio is *big*, whereas the short side is *small*, which runs counter to the idea that small stocks outperform large stocks:
    a. As marginal stocks are more common in portfolios comprised of small stocks relative to portfolios comprised of big stocks, I opted for the latter: in times of economic distress, as well as during prolonged periods of steady, albeit slow economic growth, a portfolio comprised of *big value* stocks should be able to better withstand the pressure, offering lower volatility and thus rewarding the investor when most needed.

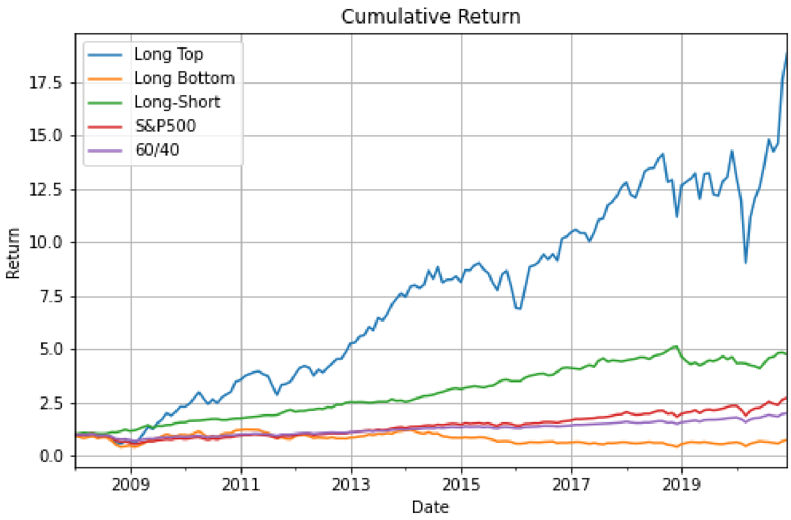
The fundamental attribute that underpins portfolio construction – the book-to-market ratio – is still assumed as the yardstick by which the quality of a stock is measured, which does not therefore mean a departure from Fama and French's HML framework.

Table 8 - Strategy overview (V)

Size (ME) breakpoint Median Market Equity (ME)		**Book-to-Market (BE/ME) breakpoints**
Small Value	**Big Value (Losers are kept)**	90%
Small Neutral	Big Neutral	
Small Growth (Winners are sold short)	Big Growth	10%
*Long/Short = 1/2 * Big Value (losers) – 1/2 * Small Growth (winners)*		

2.5.3 Performance Overview

Figure 4 – Strategy returns (V)



The long side of the strategy performs fairly well the entire sample period, with an average annual return of roughly 27.33%. Conversely, the short side of the strategy, as a standalone long investment strategy, offered an average annual return of 2.4%. The benchmark portfolios, the SPDR S&P500 ETF Trust (SPY) and a 60/40 portfolio - weighted 60% in the S&P500 (SPY) and 40% in Vanguard's Total Bond Market ETF (BND) - , offer average annual returns of 11.04% and 5.79%, respectively. The Long-Short portfolio offers a higher average annual return of 12.47% relative to the S&P500 benchmark portfolio while entailing a lower level of volatility of around 9.54% (versus 15.80%). The benchmark 60/40 portfolio implies a similar level of volatility relative to the Long-Short portfolio (9.71%) but falls shorter on annual returns. In other words, the Long-Short portfolio offers a greater reward (excess return) per additional unit of risk, with a Sharpe Ratio of 1.31 (versus the S&P's 0.66 and the 60/40's 0.79). The Long-Short portfolio comfortably (cumulatively) outperforms both the S&P500 and 60/40 benchmark portfolios throughout the entire sample period. Please find a summary of performance metrics in the table below (long and short portfolios are henceforth designated 'Top' and 'Bottom', respectively):

Table 9 - Summary of Performance Statistics (V)

	Long Top	Long Bottom	Long-Short	S&P500	60/40
Annualized Return (%)	27.33%	2.40%	12.47%	11.04%	5.79%
Annualized Volatility (%)	30.65%	30.48%	9.54%	15.80%	9.71%
Sharpe Ratio	0.8736	0.0605	1.3065	0.6636	0.7925
Skewness	0.4684	0.2490	-0.5378	-0.6461	-0.6892
Kurtosis	3.1975	1.6049	1.8784	1.4739	2.2812
Positive Months (%)	66.67%	48.08%	71.15%	64.74%	62.18%
Cumulative Return (%)	1884.96%	75.02%	473.06%	271.31%	199.26%
Max. Drawdown (%)	45.27%	66.68%	20.07%	47.31%	31.23%

In line with the relative-distress factor theory, companies with high book-to-market ratios (more heavily discounted/ distressed firms), are intrinsically riskier, and should therefore offer higher expected returns. Conversely, companies with low book-to-market ratios, perceived as safer, should offer lower expected returns. This rationale is behind the choice of losers and winners: losers with high book-to-market ratios should consistently win over the course of time, and winners with low book-to-market ratios should experience persistent losses. This is indeed the case: albeit not the optimal choice on a risk-adjusted basis, the ‘Top’ portfolio eclipses those of all other alternative strategies concerned in terms of cumulative performance. Liquidity shocks, or mismatches between supply and demand of certain stocks within this cohort, can be partially to blame for the losses they experience more seldomly than not. On the other hand, the ‘Bottom’ portfolio, comprised of stocks of firms with low book-to-market equity, performs poorly throughout the entire sample period. Investor overreaction (optimism), or the previously mentioned cognitive errors, as the driver of recent gains, fades away when these very same investors start discounting from stock prices the fundamentally poor earnings prospects of such stocks; it might be the case that investors take their time to adjust to new information. While the Covid-19 pandemic dented the performance of the market as a whole, big value stocks on the long side and small growth stocks on the short side cushioned the strategy against the market turbulence felt during the 2008 financial crisis. Finally, 3- and 5-

factor Fama French regression analysis attest to the significance of both HML and SMB factors in explaining the returns of the Long-Short strategy. The former responds positively, and the latter responds negatively, as expected. The R^2, that gauges the explanatory power of the model, is unquestionably low, which begs the question of which other factors can be driving the returns of the Long-Short strategy. For more details on the performance of the strategy, please see the individual report on Value, Distress, and Short-Term Reversal.

3. Combined Strategy

The aim of most investors is to construct a portfolio that provides the best return for a certain level of risk. Some strategies attract investors with high total returns; however, the returns can become unattractive when the associated risk is disproportionally high. Hence, it is important to measure the performance on a risk-adjusted basis, for example with the Sharpe Ratio. The advantage of the Sharpe Ratio is that it not only considers the return of an asset but also incorporates the risk. Therefore, the best way to combine our strategies is to find the combination that yields the highest risk-adjusted return, meaning that we aim to maximize the Sharpe Ratio. We consider each strategy and their corresponding returns as an individual asset which will be part of a diversified portfolio. Moreover, four strategies include equities, and one includes commodities, which is beneficial since commodities and equities have not been highly correlated historically. The next subsections will discuss how we implement our asset allocation and construct the optimal portfolio.

3.1 Strategies summary

Table 10 - Strategies Summary

	Strategy 2 (SCS)	**Strategy 3 (LVS)**	**Strategy 1 (CMD)**	**Strategy 4 (ESI)**	**Strategy 5 (VDS)**
Sharpe Ratio	0.67	0.64	0.56	0.41	1.22
Average Excess Return	8.7%	11.7%	3.8%	5.6%	10.3%
Standard Deviation	12.98%	18.2%	6.7%	13.6%	8.4%
Cumulative Return	145.7%	210.1%	46.3%	65.2%	188.9%

Table 10 shows key statistical measures for every strategy.

Table 10 presents a summary of the individual strategies and their respective performance statistics. Most of the individual strategies show a similar performance, with the Sharpe Ratio ranging between 0.41 and 0.67. The Value, Distress and Short-Term Reversal strategy (VDS) is an outlier in our sample and delivers the best risk-adjusted performance with a Sharpe Ratio of 1.22. At first glance, the well-below-one Sharpe Ratios, which approximately match that of the S&P 500 index, might look underwhelming. However, some interesting characteristics about each strategy can increase the attractiveness of our combined portfolio. For instance, the strategies do not show much correlation with each other. Moreover, while the LVS strategy (3) and ESI strategy (4) experienced noticeable drawdowns during the COVID-19 crisis, the SCS strategy (2) performed well and the CMD strategy (1) remained virtually flat (Figure 5). Such behavior reduces the portfolio volatility and is highly desirable. Hence, in the next step it is important to find a good allocation mix so that the diversification effect can be maximized.

Figure 5- Cumulative Performance Comparison

3.2 Correlation matrix

The correlation matrix in Table 11 shows the correlation coefficient between the individual strategies. The highest observed correlation is only 0.15. Since no strategy is strongly correlated with another, the overall portfolio risk can be reduced, allowing for the construction of a well-diversified portfolio. In the following chapter we will explain how our optimal portfolio was constructed.

Table 11 – Correlation Matrix

	Strategy 2 (SCS)	Strategy 3 (LVS)	Strategy 1 (CMD)	Strategy 4 (ESI)	Strategy 5 (VDS)
Strategy 2 (SCS)	1.000	0.148	0.088	0.034	-0.243
Strategy 3 (LVS)	0.148	1.000	0.145	-0.044	0.034
Strategy 1 (CMD)	0.088	0.145	1.000	0.033	-0.023
Strategy 4 (ESI)	0.034	-0.044	0.033	1.000	-0.077
Strategy 5 (VDS)	-0.243	0.034	-0.023	-0.077	1.000

Table 11 shows the returns correlation matrix between the five individual strategies.

3.3 Portfolio Optimization

The optimal asset allocation is calculated for a diversified portfolio with the goal of obtaining the optimized relation between risk and return by maximizing the Sharpe Ratio. It is nonetheless important to mention that while the obtained weights are used as a proxy for future returns, they are based on past returns.

The portfolio optimization follows the model pioneered by Markowitz (1952). Thus, the group decided to simulate one million different weights combinations and calculate their corresponding annual returns and volatilities. As previously mentioned, the combination with the highest Sharpe Ratio is the optimal combination.

Figure 6 - Efficient Frontier Plot

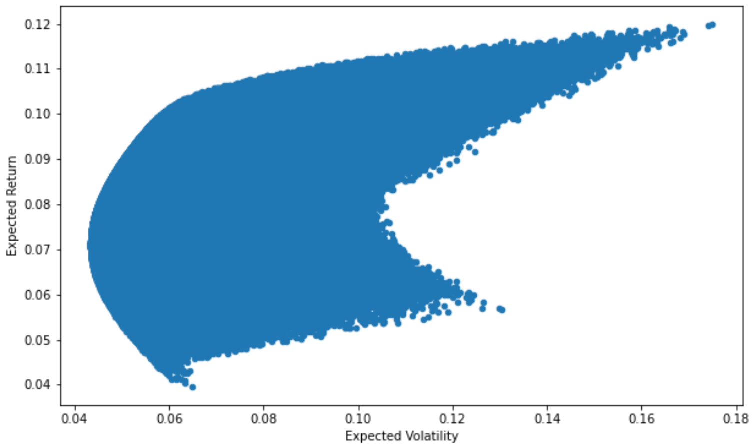


Figure 6 shows one million expected return and expected volatility combinations of the strategies. The combinations on the frontier above the global minimum-variance portfolio represent the so-called efficient frontier which includes all combinations that have the lowest volatility for a given expected return.

Looking at Figure 6, the expected volatility at the leftmost position in the expected volatility axis corresponds to the global minimum-variance portfolio, which offers the lowest possible volatility and for a given return. The risk-return opportunities of the minimum-variance frontier above the global minimum-variance portfolio lie on the so-called efficient frontier. The combinations of assets on this frontier yield the best risk-return combinations, making them potential optimal asset combinations. The portfolios below the global minimum-variance portfolio are not efficient, since there is always a portfolio laying on the efficient frontier that offers a higher expected return for the same amount of risk. It is also important to notice that all individual strategies lie inside the minimum-variance frontier if short-selling in the construction of the risky portfolio is allowed, which emphasizes the effect of diversification and shows that investing in a single strategy might be inefficient.

In the next step of the optimization process, we present the asset combination resulting from the simulations. It is the highest risk-return combination which offers the highest Sharpe Ratio. Moreover, we determine the weight of each strategy within our optimal combination which can be seen in Table 12.

Table 12 - Optimal Weights

Strategy	**Strategy 1 (CMD)**	**Strategy 2 (SCS)**	**Strategy 3 (LVS)**	**Strategy 4 (ESI)**	**Strategy 5 (VDS)**
Weight	17.1%	20.2%	6.5%	9.8%	46.4%

Table 12 shows the weights of the individual strategies within the optimized portfolio.

As shown in Table 12, the optimized portfolio would invest 20.2% in the SCS strategy (2), 6.5% in the LVS strategy (3), 17.1% in the CMD strategy (1), 9.8 % in the ESI strategy (4), and 46.4% in the VDS strategy (5). Lastly, from this point onwards, all the analysis will designate the optimal portfolio as the group portfolio.

3.4 Optimized Portfolio Statistics

To see how the optimization process can enhance portfolio returns, the *Group Portfolio* will be compared with an equal-weighted portfolio comprised of the five individual strategies.

Confirming our initial expectations, the Group Portfolio outperforms the equal-weighted benchmark on all performance metrics, which can be seen in Table 13.

Table 13 - Group Portfolio Vs Equal-Weighted Statistics

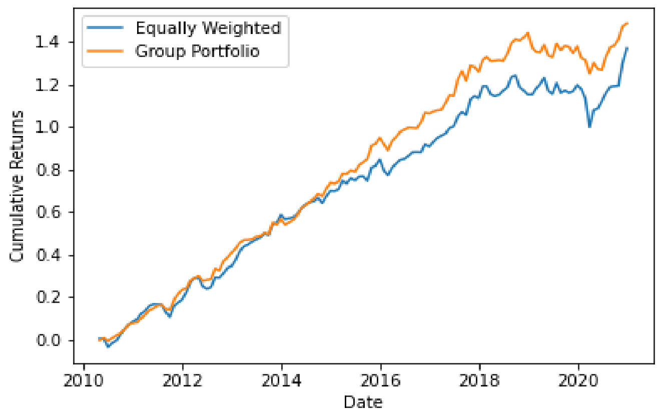
(Annual)	Equal-Weighted	Group Portfolio
Cumulative Return	136.90%	148.58%
Mean	8.20%	8.48%
Volatility	5.83%	4.81%
Sharpe Ratio	1.4	1.76
Skewness	-0.94	-0.1
Kurtosis	2.17	0.10
Max Drawdown	-10.84%	-8.44%

Table 13 shows several performance measures for the Equal Weighted portfolio and the optimized Group Portfolio. The statistics are based on monthly returns and the reported Mean, Volatility and Sharpe Ratio are annualized.

The Group Portfolio has a better risk-adjusted return in comparison with the equal-weighted benchmark, which is unsurprising following the optimization process. Kurtosis is lower, while skewness is higher in the Group Portfolio. Maximum drawdown, an important measure of portfolio risk management, was lower in the Group Portfolio relative to that of the equal-weighted benchmark.

Figure 7 shows the cumulative return of the equally weighted and group portfolio. There was not a sizable difference between the two portfolios with regards to cumulative performance. After trending closely from the beginning through half of the sample period, the Group Portfolio started outperforming the equal-weighted portfolio. Moreover, the equal-weighted benchmark is more volatile and thus riskier; during periods of market uncertainty, the equal-weighted benchmark underperformed relative to the Group Portfolio. Portfolio optimization thus resulted in a more robust portfolio, more capable of withstanding times of market uncertainty.

Figure 7: Equal Weight vs. Group Portfolio



4. Performance analysis

4.1 Methodology

For the performance analysis, the time period between April 2010 and December 2020 was chosen. This choice reflected, to an extent, data availability constraints for the Short-Sale Constrained Stocks (SCS) strategy (2). In order to test the consistency of the performance and to prevent data mining, we also conducted an out-of-sample analysis for the time periods ranging from April 2010 to December 2015 and from January 2016 to December 2020.

The main goal of our analysis is to assess whether the performance can be justified by the associated risk. Hence, the most relevant performance indicator is the widely accepted Sharpe Ratio measure developed by Sharpe (1966).

The Sharpe Ratio is computed as shown in equation 1.

$$S_i = \frac{R_i - R_f}{\sigma_i} \tag{1}$$

Where R_i is the return for the portfolio i, R_f is the risk-free rate, and σ_i is the standard deviation of the rate of return for portfolio i during the time period. This formula provides us with the risk premium return earned per unit of total risk. The risk-free rate was obtained from the Fama-French factors data source at Dartmouth´s website. For zero-cost portfolios in our combined strategy we use only R_i in the denominator of the formula.

Moreover, we will assess the maximum drawdown of the strategy which is the maximal peak-to-trough decline during the sample period that puts the investor in an uncomfortable situation. In addition, we will examine the correlation of the strategy to the U.S. equity market. For this purpose, the S&P 500 index (SPY) will be used as a proxy which consists of the 500 leading U.S. companies, covering approximately 80% of the U.S. market capitalization (Spglobal 2020). The correlation matters in particular to investors who are invested in other assets than our proposed strategy. A low correlation with the market would be a desirable characteristic as it would diversify the overall portfolio. Finally, we will incorporate transaction costs like trading fees, bid-ask-spread and slippage/latency to test how robust the strategy behaves under more realistic assumptions.

Furthermore, we will compare the combined portfolio to other conventional portfolio allocations. The most prominent is the 60/40 portfolio which consists of 60% in equities and 40% in bonds. The question of whether this long-time proven portfolio allocation is up to date is quite important. The original idea of this portfolio allocation was to have income from bonds during recessions which would compensate for poor equity performance. Nowadays, bonds offer very low yields compared to the historical average, casting doubt on whether this portfolio construction remains relevant. Our combined strategy could potentially serve as an alternative as it does not include bonds. The diminishing yields in the bonds market led investors to alternative assets seeking diversification and yield. Real estate and commodities are popular asset classes to diversify portfolios with. As real estate is highly illiquid, not accessible through the capital markets (with the exception of REITs), it is not suitable for a systematic portfolio strategy. Exposure to commodities, on the other hand, is easily accessible through the financial market. We will therefore compare our strategy to an 80/20 portfolio which consists of 80% of the S&P 500 index and 20% of the GSCI index. This particular allocation was chosen because our combined strategy also shows an approximately 17% exposure to commodities through the commodities strategy.

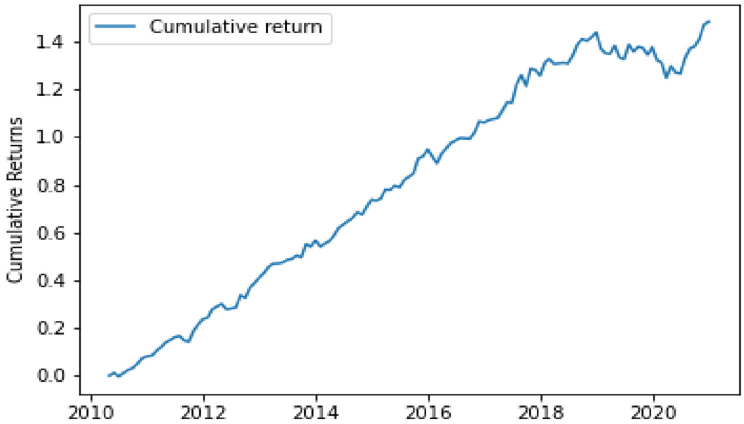
Finally, we will compare our strategy to a conservative risk parity portfolio targeting a volatility of 7% per year. The risk parity portfolio consists of the S&P 500 index as well as the iShares 3-7 Year Treasury Bond ETF (IEI). We will use a rolling 20-day standard deviation average window to dynamically adjust the weights of the SPY and IEI. In times of volatility, the weights of the IEI will increase and vice versa. It should be noted that this portfolio will only serve as a reference to a conservative portfolio as it provides the best return for a given a level of risk. Our strategy aims for maximal returns with the lowest possible risk. Finally, to make our results robust we will control for reasonable transaction costs.

4.2 Analysis

The first part of the analysis will focus on the gross returns during our sample period between April 2010 and December 2020. Table 14 exhibits various performance statistics for different portfolio allocations and shows an initial cumulative gross performance of our strategy of 149% with an annual standard deviation of 4.81%. That results in a Sharpe Ratio of 1.76 which certainly is a great performance. One statistic that stands out is the very low standard deviation of below 5% considering that the strategy has about 83% exposure to the U.S. equity market. Moreover, Table 10 shows the standard deviations for the individual strategies which are substantially higher, 12% on average. The large difference in volatility indicates how effective the portfolio optimization is and how helpful the low correlations between the strategies are to effectively reduce portfolio risk.

Figure 8 presents the cumulative return of our combined strategy. The graph clearly shows a steady uptrend with minimal drawdowns. In fact, the maximum drawdown was approximately - 8.44% and happened during the COVID-19 crash in March 2020. To put it into perspective, global indices like the S&P 500 index or the DAX have dropped between 30% and 40% in the same period. Ultimately, the low volatility of 4.81% and the small drawdown

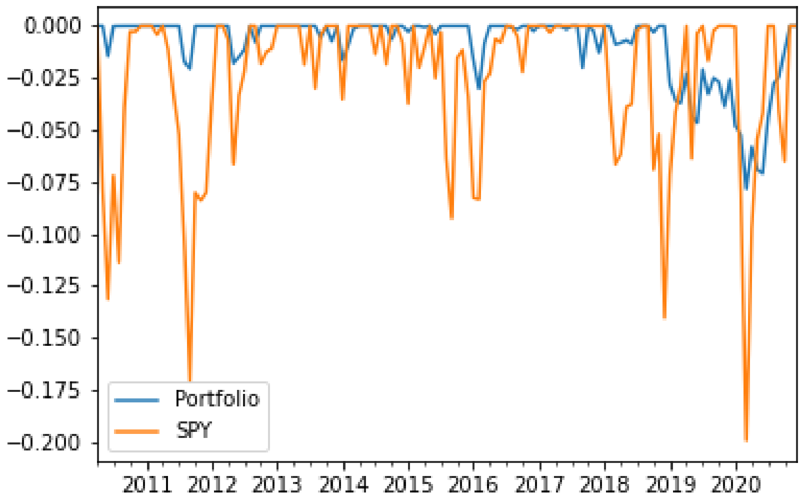
Figure 8: Group Portfolio Cumulative Performance



support the Sharpe Ratio of 1.76 and indicate that this strategy is quite resistant to market shocks despite having much equity exposure. Considering somewhat volatile equity markets, which have been affected by the COVID-19 crisis, FED uncertainty to raise interest rates and fears steaming from the trade wars and broader geopolitical disputes between the United States and China around 2018, a worst month performance of -2.85% is remarkable.

Figure 9 illustrates the drawdowns of the S&P 500 index and of our combined strategy. While our strategy clearly shows a similar pattern with that of the S&P 500 index, the effects are less severe. Please note that the drawdowns relate to our monthly data series. This means that this chart underestimates the real drawdown experienced intra month. For instance, and as stated above, the S&P 500 index dropped slightly above 30% during the COVID-19 crash if looking on a daily timeframe.

Figure 9 - Drawdown Group Strategy & SPY



In the next step we will evaluate the relative performance of our strategy compared to the 60/40 allocation method, the 80% equity and 20% commodity, and the risk parity portfolio.

Table 14 - Comparison between Portfolios

	Group Portfolio	Gr. Portfolio Net	SPY	Risk Parity	60/40	80/20
Total Return	148.58%	107.92%	219.56%	33.60%	122.60%	149.34%
Average Return	8.48%	6.94%	11.33%	2.21%	7.28%	9.03%
Stdv	4.81%	4.79%	14.12%	2.62%	8.12%	14.23%
Sharpe Ratio	1.76	1.45	0.80	0.85	0.90	0.63
Excess kurtosis	0.10	0.09	1.10	-0.12	0.93	1.70
Skew	-0.10	-0.09	-0.32	-0.09	-0.15	-0.51
Best month	4.12%	3.98%	12.70%	2.10%	7.62%	11.48%
Worst month	-2.85%	-2.93%	-13.00%	-1.71%	-6.86%	-15.81%
Positive month	70.54%	68.22%	67.44%	55.04%	65.12%	63.57%
Max drawdown	-8.44%	-9.75%	-19.92%	-2.75%	-10.64%	-24.29%

Table 14 shows several performance measures for the optimized Group Portfolio (gross and net of transaction costs) relative to considered benchmark portfolios. The statistics are based on monthly returns and the reported Mean, Volatility and Sharpe Ratio are annualized.

Probably the most eye-catching value in Table 14 is the good performance of the S&P 500 index which was able to provide a total return of 219% in only ten years. Not only did the SPY provide great returns, but the associated risk was very acceptable, which the 0.80 Sharpe Ratio reflects. It should be noted that such performance is an outlier. Our sample period starts on the aftermath of the 2008 Global Financial Crisis (GFC), causing valuations to fall and creating upside potential. Moreover, the S&P 500 index consists of the largest companies by market capitalization which, to a large extent, happen to be technology companies. The COVID-19 crisis and the corresponding social distancing measures, travel restrictions, home office/schooling, etc. changed the consumer behavior and benefitted large tech companies. In addition, growth tech companies benefitted from the low interest rate environment since most of their valuation is derived from future earnings discounted by the relatively cheap cost of capital. Even though these considerations are beyond the scope of this report, they encapsulate our argument well: one should not be too strict if a portfolio underperformed the SPY in total return during its best decade ever. This becomes even more visible in Figure 10.

However, the group strategy outperformed all studied asset allocation methods in terms of the risk-adjusted return which is presented in Figure 11. This figure was designed by setting the standard deviation of the SPY as the basis of 100%, other returns were scaled according to their ratio. In this figure, the SPY is the second worst strategy. As the S&P 500 is a long only index, returns are unsurprisingly negative during recessions. Conversely, our combined portfolio utilizes long-short strategies which are able to generate returns during periods of recession as well as economic expansion. Hence, in terms of risk-adjusted returns our strategy comfortably outperformed the SPY with a Sharpe Ratio of 1.76 compared to 0.80 for the SPY.

Figure 10 – Cumulative Performance

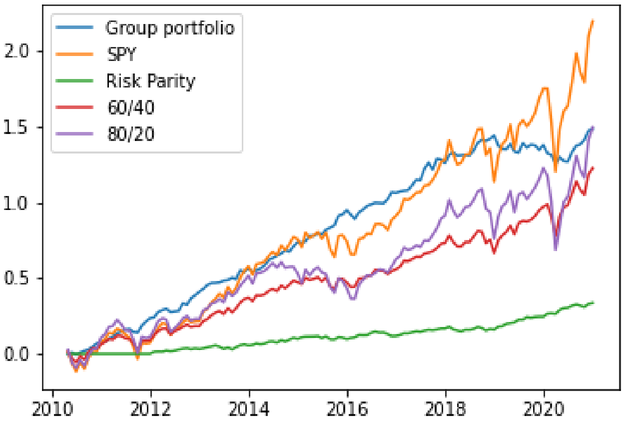
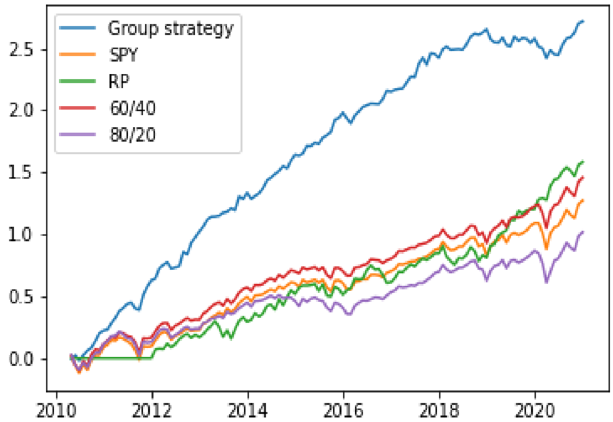


Figure 11 - Volatility normalized return



The risk parity portfolio, which dynamically rebalances the S&P 500 index and the iShares 3-7 Year Treasury Bond ETF (IEI) targeting a 7% annual volatility, also presents good results and in terms of risk-adjusted returns with the second highest Sharpe Ratio of 0.85. This strategy, however, returned only 33.60% over the last decade which is substantially lower than all other asset allocations. Nonetheless, by using leverage and SPY & bonds futures this strategy could generate SPY-like returns while maintaining the high Sharpe Ratio of 0.85. The negative skew of only -0.09 is higher than the rest which supports the argument of this strategy being very defensive.

The widely known 60/40 asset allocation consisting of the SPY and IEI exhibits a Sharpe Ratio of 0.9 which is also below our Sharpe Ratio. In terms of absolute performance, the 60/40 asset allocation provided a 123% return which is also below our total gross return but above our net return. However, the additional performance comes at the cost of increased risk which results in a lower Sharpe Ratio of 0.9. It should be noted that the high absolute performance is not surprising as 60% is allocated to the SPY. The inclusion of bonds reduced the average return while reducing the volatility to a bigger extent.

The last asset allocation we will discuss is the 80% equities and 20% commodities. This asset mix in particular is interesting because approximately the same weight applies to our combined strategy (83% U.S. equities, 17% GSCI commodities). Hence, it is worth exploring if an investor who simply hedges 20% of his broad equity exposure with a broad long only commodity index can beat our combined strategy which systematically invests in equities and commodities. Table 14 shows that the 80/20 strategy performed the worst from all asset allocations on a risk-adjusted basis (Sharpe Ratio). The total return of 149% as such is impressive and the second highest in the sample, however, comes mainly from the 80% SPY allocation. Hence, the inclusion of the commodity index comes at the expense of the returns and the standard deviation remains almost exactly the same. As a result, the Sharpe Ratio displays only 0.63 and leads to the conclusion that a commodity index does not improve the portfolio performance. Also, the most negative skew of -0.51 and a monthly maximum drawdown of -24% do not impress. In contrast, our strategy which applies almost the same weights to the asset classes equity and commodity achieves an average annual standard deviation of 4.81% whereas the 80/20 achieves a substantially higher 14.23%. We can conclude that long only commodities are not suitable to effectively hedge equity risk, instead long-short strategies should be applied.

In the following we will analyze the combined strategy by incorporating transaction. Since our backtest uses non-executable closing prices, we want to prevent biased results, therefore we account for the bid-ask-spread, slippage and brokerage fees by reducing our gross returns by the transaction costs. For the commodity futures strategy, which rebalances illiquid futures contracts on a weekly basis, we have assumed 12 basis points transaction costs per trade.

For the remaining strategies, we assumed monthly transactions costs of 20 basis points for long-only strategies and 25 basis points for long-short strategies, which are both rebalanced monthly. According to Edelen (2007), the monthly transactions costs for mutual funds based in the U.S. is 12 basis points per month. Since some strategies incorporate short selling, we adjusted the transaction costs accordingly. The estimated transaction costs for long-short portfolios tend to be higher due to the relatively high fees for short selling. These costs are especially high when the short selling demand of a stock is high or when the supply of a stock is limited (for example, small firms with a low level of institutional ownership, tend to have higher fees for short selling).

Figure 12- Gross vs. net performance

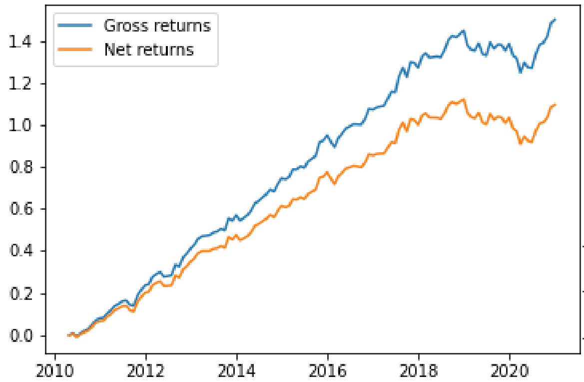


Figure 13- 6m rolling correlation

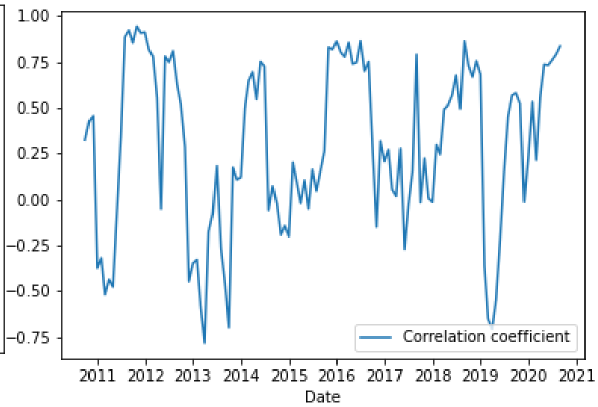


Figure 12 illustrates the noticeable impact of transaction costs on the gross performance. The total return decreases from 149% to 108% and brings down the Sharpe Ratio by 17% from 1.76 to 1.45. The importance of transaction costs becomes visible in particular from 2016 onwards. During the first part of the sample, returns were extraordinary and compensated the costs well, however, once the steepness of the performance began to decline (2016), the spread between the gross and net performance increased drastically. This is because transaction costs magnify negative returns and therefore should always be considered in backtesting. Nonetheless, even when accounting for transaction costs, our strategy by far provides the best risk-adjusted return with a Sharpe Ratio of 1.45.

Finally, we want to assess if our strategy is suitable for investors who are also passively invested in the U.S. equity market by having exposure to the SPY. The correlation between the SPY and our strategy is 0.39 and the 6-month rolling correlation coefficient is presented in Figure 13. Overall, the correlation is quite volatile, however, in light of our 80% equity exposure a 0.39 correlation can be considered good. Hence, our strategy can be used in combination with the SPY without increasing the systematic risk too much.

4.4 Out-of-Sample Performance Analysis

In this section, we analyze the performance in different time periods in order to test whether our portfolio performance is consistent. Therefore, we split the sample into two new time periods and maintain the initial portfolio weights: the first period dates from April 2010 to December 2015 and the second one from January 2016 to December 2020.

Table 15 shows the performance measures based on the data of the first out-of-sample period (April 2010 to December 2015). The VDS Strategy has the highest Sharpe Ratio (2.02) followed by the SCS strategy which has a Sharpe Ratio of 1.31. Moreover, the SCS strategy has the highest average returns in this period with 14.42% followed by the VDS-strategy (13.44%).

Table 15 – Individual Strategy Performance (First Period)

	Strategy 2 (SCS)	**Strategy 3 (LVS)**	**Strategy 1 (CMD)**	**Strategy 4 (ESI)**	**Strategy 5 (VDS)**
Sharpe Ratio	1.31	0.85	0.95	0.63	2.02
Average return	14.42%	12.72%	5.84%	7.78%	13.44%
Standard Deviation	10.97%	15.05%	6.12%	12.44%	6.65%

Table 15 shows for the first out-of-sample period several performance measures. The Sharpe Ratio, Average Return and Standard Deviation are annualized.

In the second out-of-sample period from January 2016 to December 2020, the overall performance of the strategies is significantly worse compared to the first half of the sample. Strategy 5 performs again very well with the highest Sharpe Ratio (0.66) followed by LVS strategy with a Sharpe Ratio of 0.49. The lowest ratios have the SCS strategy (0.14) and CMD strategy (0.19), whereas the SCS strategy had the second highest and the CMD strategy the third highest SR in the first half.

Table 16 - Individual Strategy Performance (Second Period)

	Strategy 2 (SCS)	Strategy 3 (LVS)	Strategy 1 (CMD)	Strategy 4 (ESI)	Strategy 5 (VDS)
Sharpe Ratio	0.14	0.49	0.19	0.21	0.66
Average return	2.13%	10.57%	1.39%	3.09%	6.60%
Standard deviation	14.84%	21.45%	7.36%	14.80%	9.96%

Table 16 shows for the second out-of-sample period several performance measures. The Sharpe Ratio, Average Return and Standard Deviation are annualized.

Table 17 compares several performance measures for the two out-of-sample periods. The Total Return of the first sample part is with 94.76% about 3.7 times higher compared to the second out-of-sample period. The Average return in the first half (11.74%) is also higher than in the second half (4.72%) and the Standard Deviation is lower in the first part (4.23%) compared to the second part (5.14%). Consequently, the Sharpe Ratio of the first part (2.72) is higher than in the second part (0.92).

Figure 14 also shows how the first out-of-sample period is characterized by a post global financial crisis recovery rally for both the SPY and our group portfolio. Certainly, the second out-of-sample period was overshadowed by more market uncertainties, amongst others the COVID-19 pandemic which to some extent may serve as an explanation for the worse performance in absolute terms. This out-of-sample analysis also indicates some pitfalls of our strategy. Comparing the performance to the SPY, one can see that it actually increased its SR from 0.76 to 0.84 despite COVID-19. In addition, SPY is a long only index which by definition can only provide negative returns during a market crash. Conversely, our group strategy utilizes a long-short approach which should perform better during such times.

Although our Sharpe Ratio (0.92) is higher than the of the SPY (0.84) for the second part, one has to remember that we are using gross returns for this analysis and overestimate our results. With transaction costs we would not beat the SPY in the second period and the question could arise whether our full-sample results are robust or if the strategy is biased by outliers from the first period. This question is not easy to answer as certainly some strategies provided paramount risk-adjusted returns during the first period with Sharpe Ratios of 2.02 (VDS) and 1.31 (SCS) but delivered Sharpe Ratios of only 0.66 (CDS) and 0.14 (SCS) during the second period. The SPY on the other hand was a steady performer with a SR of 0.76 and 0.84, respectively.

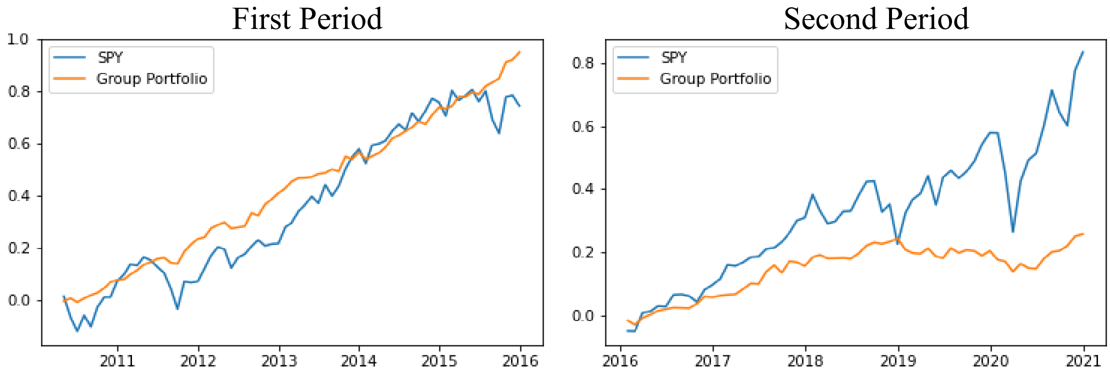
To conclude, our individual strategies have clearly been post-global financial crisis winners, providing great returns. However, the momentum started to fade during the middle of our in-sample-period. Our group portfolio outperforms the SPY in both periods, but we fail to find consistency in our results which was the initial goal of the out-of-sample analysis. Unfortunately, as mentioned before, data availability constraints make further out-sample-analyses prior 2010 impossible.

Table 17 - Out-of-sample analysis

	Group Portfolio First	Group Portfolio Second	SPY First	SPY Second
Total Return	94.76%	25.76%	74.25%	83.39%
Average return	11.74%	4.72%	10.02%	12.83%
STDEV	4.32%	5.14%	13.11%	15.30%
Sharpe Ratio	2.72	0.92	0.76	0.84
Excess kurtosis	0.47	-0.41	0.09	1.64
Skew	0.16	-0.10	-0.07	-0.51
Best month	4.12%	3.61%	10.91%	12.70%
Worst month	-1.79%	-2.85%	-7.95%	-13.00%
Positive month	43.41%	27.13%	34.11%	33.33%
Max drawdown	-2.06%	-8.44%	-17.06%	-19.92%

Table 17 presents several performance measures for the two out-of-sample portfolios. The values are annualized.

Figure 14- Out-of-sample performance comparison



5. Regression Analysis

In this section, we use the Capital Asset Pricing Model (CAPM), Fama-French Three Factor model as well as the Fama-French Five Factor model to determine the exposure of the strategy to certain factors. Table 18 shows the regressions results of the three mentioned regressions models. We consider the values of the regression as statistically significant if the p-value is equal to or less than 0.05, meaning that we can reject the null hypothesis with a confidence level of 95%. Therefore, the analysis covers only statistically significant coefficients and the explanatory power of the model (R-Squared). R-Squared tells us which portion of the strategies' variance can be explained by the factors of the model.

Table 18 - Regressions

CAPM	Full Sample	First Half	Second Half
Alpha	0.070 (0.000)	0.102 (0.000)	0.031 (0.164)
Mkt - RF	0.121 (0.000)	0.123 (0.001)	0.122 (0.002)
N	129	69	60
R-Squared	0.139	0.147	0.288
FF3	**Full Sample**	**First Half**	**Second Half**
Alpha	0.076 (0.000)	0.103 (0.000)	0.042 (0.060)
Mkt - RF	0.139 (0.000)	0.140 (0.001)	0.146 (0.001)
SMB	-0.142 (0.005)	-0.119 (0.079)	-0.164 (0.029)
HML	0.143 (0.001)	0.092 (0.215)	0.154 (0.009)
N	129	69	60
R-Squared	0.231	0.201	0.269

FF5	Full Sample	First Half	Second Half
Alpha	0.077 (0.000)	0.100 (0.000)	0.046 (0.039)
Mkt - RF	0.132 (0.000)	0.158 (0.000)	0.128 (0.007)
SMB	-0.136 (0.011)	-0.081 (0.261)	-0.185 (0.024)
HML	0.181 (0.001)	0.127 (0.189)	0.221 (0.002)
RMW	0.047 (0.531)	0.161 (0.151)	-0.054 (0.658)
CMA	-0.124 (0.162)	-0.041 (0.772)	-0.216 (0.079)
N	129	69	60
R-Squared	0.245	0.227	0.314

Table 18 shows the regression results using the CAPM, Fama-French Three Factor model and the Fama-French Five Factor model. The regressions are calculated using the full sample (in-sample) and the first and second half (out-of-sample). The Alpha values are annualized, and the corresponding p-value is indicated within parentheses.

5.1 CAPM

The CAPM considers only systematic risk (market risk) since we cannot reduce or mitigate this kind of risk through diversification. On the other hand, unsystematic risk is unique to the company (for example, management issues or the risk of new competition in the market) and can be diversified away or mitigated. The beta of the regression (in Table 18 named: Mkt – RF) describes the sensitivity between our strategy and the market. Therefore, a beta of 1 means that when the market increases by 1%, our strategy will on average also increase by 1%. In the case of a negative beta of -1.2, our strategy will decrease on average by 1.2% when the market increases by 1%. The alpha of the regression can be interpreted as the average return of the optimized portfolio that cannot be explained by the risk factor. It is also the intercept of the regression.

The results in Table 18 show that in the full sample, the annualized Alpha equals 7.0% with a low market exposure of 0.121. Therefore, the group strategy is not highly correlated to the market, meaning that when the market increases by 1%, the group strategy will on average increase by 0.121%. In the first sample period, Alpha has a significant value of 10.2% which is in line with the results in the previous section, where the first half performed the best. The corresponding beta in this period is a bit lower than in the full sample but still low (0.123). In the second half, only beta is significant (0.122), which is in line with the other periods.

Moreover, the regression model also presents the corresponding R-squared. The values of all periods are relatively low, meaning that the CAPM-factors can only explain a small portion of the group strategy's variance.

5.2 Fama-French Three Factor Model (FF3)

The Fama-French Three Factor Model (FF3M) expands the CAPM by adding two more factors: SMB and HML. SMB (Small minus Big) captures the outperformance of small over large companies and HML (High minus Low) captures the outperformance of value over growth stocks. The regression values for the full sample are all statistically significant, with an Alpha of 7.6% and a low market exposure of 0.139. The SMB factor equals -0.142, meaning that the group strategy has a low negative exposure towards small caps. The HML factor of 0.143 for the full sample suggests that the group strategy behaves to a low degree like a strategy with exposure to value stocks. In the first out-of-sample period, the alpha (10.3%) and beta (0.140) are the only significant values and do not differ much from the values of the full sample period. The regression values of the second part of the sample suggest that the group strategy has a low market exposure (0.146) and low exposure to the HML factor (0.154), in line with the other periods. The R-Squared of the regression is for each period higher than in the CAPM regression, meaning that the FF3 factors can explain a higher portion of variance of the group strategy.

5.3 Fama-French Five Factor Model (FF5)

In the last regression, we use the Fama-French Five Factor Model (FF5M) which adds another two factors to the FF3M: RMW and CMA. The RMW (Robust minus Weak) factor captures the return spread between the most and least profitable firms, while the CMA (Conservative minus Aggressive) factor captures the return spread between firms that invest conservatively and firms that invest aggressively. The regression results in Table 18 show for the full sample significant values except for the RMW and CMA factors. The significant values do not differ much from the ones obtained in the FF3 regressions. The same is true for the first half, in which only the alpha (10.0%) and beta (0.158) coefficients are significant. In the second half of the period, alpha (4.6%), beta (0.128), and the HML (0.221) and SMB factors (-0.185) are significant. Although the values do not change much across different regressions, the FF5 regression shows, for all time periods, the highest R-Squared, suggesting that the factors of this model explain the highest portion of variance in the returns of the group strategy. The R-Squared values in the FF5 model are still relatively low, however.

6. Implementation issues

One important cornerstone of the implementation issues investors could face relates to transaction costs. Explicit transaction costs certainly depend on the monthly trading volume and whether one has retail or professional status. Professional investors, for instance, usually enjoy lower trading costs. In the first part of the analysis, we analyze gross returns, therefore overestimating returns. Investors also bear implicit trading costs, that include the bid-ask-spread and slippage/latency. These costs are usually larger for professional investors, as the size of their positions is more likely to make them incur in slippage. In our analysis, we are using the last price per day/week/month. In a real-life setting, this price is not necessarily executable as we would need to buy at the ask or sell at the bid. The spread is not always of same size. During times of market volatility (during the early stages of COVID-19, for instance) spreads usually widen. Spreads for illiquid stocks/commodities can remain fairly large even during normal market conditions, however. Even small spreads compound over the years and can have a material effect on the performance.

Moreover, illiquidity can be a serious issue for the commodity futures strategy as it is based around distant contracts. Those in particular have the most liquidity when investors are rolling the contracts over the following month. An investor who wants to act on the trading signal, however, needs instant liquidity. Hence, the commodity strategy may underestimate the effect of illiquidity. The investment environment for commodity futures is also changing rapidly. The individual report of the commodity strategy talks a bit more about the financialization of the commodity market. In short, the market is growing exponentially, and it is yet to be seen to what extent the risk premium remains.

Additionally, most of our individual strategies require a margin account. For instance, the commodity futures strategy could not be implemented at all as futures trading requires a margin account. Other strategies that utilize a long-short approach need a margin account for borrowing the stocks. Hence, the strategy is rather difficult to implement for retail investors. Not only because increasing gross exposure to over 100% by being long and short is riskier and requires a sound understanding of financial markets, but also because of the capital needed. In order to rebalance our portfolio to achieve the optimal weights, stocks and commodity futures needs to be bought/sold. This is not an issue with stocks that usually range between \$10 – \$1000; however, when dealing commodity futures whose notional value for one contract is up to \$100,000, rebalancing can be problematic. Hence, precisely achieving the optimal weight asset allocation is only possible for institutional sized portfolios.

Survivorship bias should also be kept in mind when implementing our combined strategy. A few sub-strategies utilize a long-short approach on a variety of indices like the S&P 500 or Russell 1000. As losers are being replaced by winners in the indices, it is important to keep the losers in the investable universe as they positively contribute to the long-short strategies. Conversely, if one would always use the most up-to-date constituents list, the strategy would underperform.

Furthermore, the saying “past performance is not indicative of future returns” is widely known in the financial sector and probably truer than ever. Adding to the uncertainty of the future commodity risk premium, it is also highly unlikely that the returns of this analysis will be replicable. The considered time period commences in the aftermath of the global financial crisis and spans the best decade for equities. Additionally, it covers the post pandemic boost. Also, as our portfolio consists of a very large investable universe, the correlations between assets can change and alter the performance.

In addition, the optimization process in chapter 3.2 of this report potentially introduces a bias into our analysis. Since our optimal weights have been selected from a pool of one million different portfolio combinations, a backtest overfitting bias cannot be excluded. According to Bailey et al. (2014, 3) “the proposed strategy is only fitting idiosyncrasies in the ‘noise’ of the dataset”. Unfortunately, we cannot conduct a profound out-of-sample analysis before the year 2010 because of the previously mentioned data availability constraints. Investors using our strategy should thus be aware of this issue, closely monitoring the appropriateness of weights over time. Our strategy was tested for the decade between 2010 and 2020; while the weights may have been optimal for this period, they can change in future as the markets move in cycles.

Finally, some of the strategies covered in this report rely on fundamental data like the company earnings in order to construct the trading signal. The inconsistent availability of this data comes with the risk of the forward-looking bias in backtesting. Companies have up to 45 days to publish their quarterly results and up to 90 days to publish their full year results. However, companies can even delay their report if an audit takes longer. The common fallacy in backtesting is to act on fundamental data wit (Roger M. Edelen, Scale effects in mutual fund performance: The role of trading costs 2007)h prices from the same month. This approach will overestimate the performance since the backtest will act on fundamental data which has not been known to the public at this time. For instance, to avoid this bias, the Long-only Value Investing strategy (LVS) incorporated a conservative 3-month lag before acting on fundamental data.

7. Conclusion

The unique characteristics of each individual strategy used to construct the optimized group portfolio provides the investor with a diversified portfolio that outperforms considered benchmarks on a risk-adjusted basis throughout the entire sample period. Low correlations between the returns of each individual strategy, a low correlation between the returns of the group strategy and the market (notwithstanding a high degree of exposure to the US equities market of around 83%), within a long-short framework, helped lowering the overall volatility of the portfolio via diversification of risk. This protected the investor against uncomfortably high drawdowns during times of economic distress (like the early stages of Covid-19).

However, when looking at the results of the out-of-sample analysis, one can attest to the differences between risk-adjusted performance between the first and second halves of the sample period: whereas the group strategy more robustly handled market turbulence relative to the S&P500 benchmark between 2010 and 2015, it started to fall short from thereon. On the one hand, commodities were a safe haven for investors during the first half of the sample. On the other hand, the strategies whose construction were based on fundamental data (such as P/E ratio), may be partially to blame for a weaker performance in the second half of the sample: over the last few years, stocks traditionally deemed as overpriced based on their fundamentals (*growth stocks*) have been among the best performers in the market.

Finally, how the group strategy would behave out-of-sample (prior to 2010) is unknown, and the same is true for how the strategy might perform in the future. Combining five individual strategies with different characteristics comes with implementation issues and the increased potential of introducing a bias into the results. The portfolio manager should therefore regularly monitor the performance of the strategy in the future in order to modify it, if needed. Notwithstanding these and other limitations, we are confident that our analysis is solid, theoretically sound, and implementable.

I List of Figures

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III References

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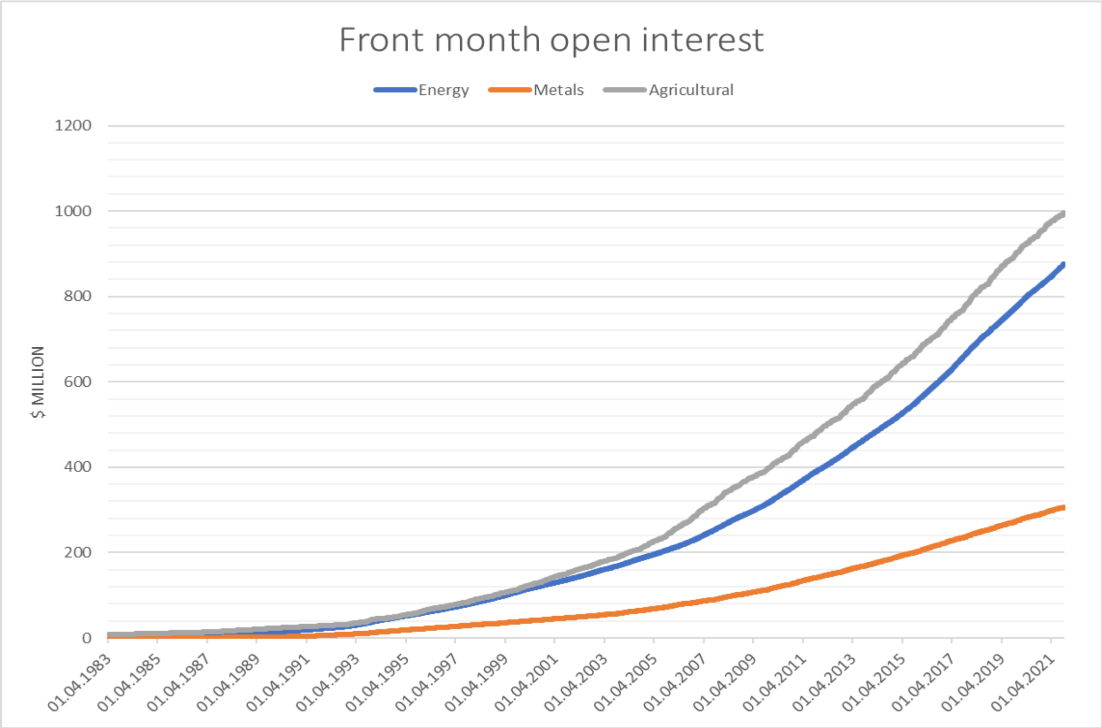
IV Appendices

Appendix 1: Futures open interest

This graph represents the open interest of the front month futures contract of the GSCI index constituents.

(Tickers: CO1, CL1, QS1, HO1, NG1, XB1, GC1, SI1, LA1, HG1, LL1, LN1, LX1, CC1, KC1, CT1, QW1, C 1, S 1, W 1, KW1, FC1, LH1)



(Author´s own rendering based on dataset obtained from Bloomberg)

Appendix 2: Commodity futures returns

This table exbibits the annualized average returns of the commodity futures at different points on the curve. Since not all commodity futures have the same variety on futures, it is not unified.

For Brent Crude Oil, WTI Crude Oil, Gasoil, Heating Oil, Natural Gas, RBOB Gasoline, Aluminum, Copper, Lead, Nickel, and Zinc it is the 8th contract.

For Gold, Silver, Corn, Soybean, Wheat, KC HRW Wheat, Feeder Cattle, Lean Hogs, and Live Cattle it is the 4th contract.

For Cocoa, Coffee, Cotton, and Sugar it is the 3rd contract.

	Front month	Second contract	Distant contract	Distant - Front
Brent Crude Oil	3.62%	1.62%	3.56%	-0.05%
WTI Crude Oil	-0.77%	-2.88%	3.81%	4.58%
Gasoil	1.90%	-0.75%	0.22%	-1.68%
Heating Oil	0.33%	-1.26%	1.26%	0.93%
Natural Gas	-22.08%	-26.93%	-10.84%	11.24%
RBOB Gasoline	12.52%	7.37%	6.76%	-5.76%
Gold	8.88%	7.87%	7.95%	-0.93%
Silver	10.68%	9.83%	10.24%	-0.44%
Aluminium	-2.76%	0.02%	2.08%	4.84%
Copper	10.02%	8.61%	11.40%	1.38%
Lead	4.64%	9.19%	10.86%	6.22%
Nickel	0.79%	8.28%	9.46%	8.67%
Zinc	0.47%	7.44%	9.22%	8.75%
Cocoa	8.54%	5.19%	5.63%	-2.91%
Coffee	1.50%	-1.34%	-0.79%	-2.29%
Cotton	2.71%	4.02%	6.24%	3.53%
Sugar	11.49%	8.02%	5.90%	-5.59%
Corn	5.49%	3.16%	4.87%	-0.62%
Soybean	11.86%	8.33%	9.44%	-2.42%
Wheat	0.58%	-2.62%	0.27%	-0.31%
KC HRW Wheat	-0.45%	-1.56%	2.14%	2.59%
Feeder Cattle	0.33%	-0.58%	2.76%	2.42%
Lean Hogs	3.46%	-6.96%	-1.25%	-4.71%
Live Cattle	6.71%	-2.58%	2.59%	-4.12%