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Analyzing the Analysts:

How does consensus move with profitability?

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Abstract

The purpose of this report is to present a quantitative strategy analysis based on the combination of an analyst's recommendation and a measure of a company's profitability, the return on equity. It tests how this combination can generate abnormal stock returns. Furthermore, it is also seen how an opposite strategy would perform. Several measures were calculated to evaluate the performance of both strategies.

A long-only strategy of reverse IBES and profitability outperform on a risk-adjusted basis the long-only IBES and profitability, with yearly excess returns of 10.49% and a Sharpe ratio of 0.34.

Keywords: Finance, Financial Markets, Fundamentals, U.S Stock Market; Performance Analysis

Introduction

Quantitative investing was established around the 70s by Sam Eisenstadt when he discovered that top stocks with higher 6-month trailing performance were outperforming the bottom-ranked stocks. As it is described in “A study of different existing methods for the stock selection in the field of quantitative investment” by Pengfei Li and Jungang Xu (2022), quantitative trading has been the domain technique to beat the market by some hedge funds, but as computational power and data have evolved, traditional investors have also begun to borrow and develop quantitative techniques, algorithms-based programs, and tools to deliver abnormal returns.

These days, most of the investment community has adopted several quantitative strategies – machine learning, advanced mathematical models, factor investing, the usage of alternative data, and many others– to outperform stocks and increase their returns when compared to an index.

This work project aims to build and analyze a quantitative investment strategy based on the Institutional Brokers’ Estimate System (IBES) estimates and one of the measures of a company’s profitability, the return on equity (ROE).

Prior studies by Womack (1996) found that an upgrade (downgrade) in a recommendation is associated with positive (negative) abnormal returns around their announcements. In addition, a paper published by the University of Illinois, “A Comparative Analysis of ROE and Value-to-Price based Trading Rules: Do Conventional Risk Factors Matter?” (2001), found that an ROE-based trading rule could generate significant returns over a 12-month period after portfolio formation.

Further sections will focus on understanding whether or not a strategy based on these two metrics could outperform the market and how differently it performs throughout the whole sample.

Literature Review

The first thing to bear in mind is that not all analysts tell you the same. Analysts predict their estimates based on earnings from each company, and economic condition but also from their models and intuition. Each eye sees it differently, thus it is expected that each analyst generates a different recommendation.

Studies by Landsman and Finger (2003) show that optimistic recommendations are derived from higher book-to-market ratios, higher market values, and lower ratios of value to price. Also, Jegadeesh (2004) in the Journal of Finance, demonstrates that analysts tilt toward high-momentum stocks and growth stocks. It also showed that higher trading volume, higher past and projected growth, more positive accounting accruals, and more aggressive capital expenditures also contribute to a favorable recommendation by the analyst.

In addition, a paper by Pilar Corredor and Elena Ferrer (2012), stated that "Investor sentiment has also been identified as a key variable in explaining analyst behavior". Investors' opinion, mostly emotionally driven by the state of the market, affects analysts. Analysts are unable to disassociate themselves from the market sentiment, which has been found to affect forecasting recommendations

IBES, also known as "I/B/E/S", refers to the Institutional Brokers' Estimate System. The IBES is a database of more than 18000 analysts' estimates and recommendations, standardized in a 1 to 5 scale, where 1 means strong buy, 2 means buy, 3 means hold, 4 means sell, and 5 means strong sell. To construct the strategy, the IBES was used to obtain the monthly average analyst recommendations.

Also used to construct the strategy is one of the measures of a company's profitability, the return on equity (ROE). The ROE is a key ratio (net income divided by shareholders' equity) for shareholders given that it measures the ability of a company to earn a return on its equity investments.

Based on the assumption that currently profitable firms have greater potential for future growth, the greater the growth potential for profits and dividends, the greater the expected future rate of return. Robert Haugen and Nardin Baker (1996), showed in "Commonality in the determinants of expected stock returns" that high-return deciles tend to include stocks with strong growth characteristics (return on equity among).

With that said, a high ROE does not always mean a positive thing and has some major drawbacks. For example, if a firm uses high levels of debt to finance its debt it might boost its ROE, but the high leverage puts the company at risk.

So, in order to improve the analysis of both individual factors and understand how and if they can provide a better performance, both metrics are used to construct the strategy. By combining both the average analysts' recommendations on a company with the return on equity of the same company, it can give us a sight of not only investing in stocks with a high return on equity but also evaluated as favorable in the eyes of the analysts, which can help eliminate any existing bias. The final factor is then computed as the sum of the return on equity announced and the recommendation provided.

Data and Methodology

Data

IBES data

The chosen source for the data was www.wharton.upenn.edu. Firstly, it was retrieved data from IBES. IBES provides data on both summary and individual analyst forecasts of company earnings, cash flow, and other important financial items, as well as buy-sell recommendations. It covers monthly US data from 01/12/1992 up to 31/09/2022, and it contains the I/B/E/S ticker of each company, the CUSIP, the IBES recommendation code (IRECCD), and the date of the recommendation.

Analysts may have different individual recommendation scales, but, as it was mentioned before, IBES standardizes recommendations as 1(strong buy), 2 (buy), 3(hold), 4 (sell), and 5 (strong sell). The order was reversed so that small numbers represent negative recommendations (1- strong sell) and higher numbers represent positive recommendations (5- strong buy). A total of 802,212 recommendations were obtained.

Return on Equity (ROE)

From Wharton Research Data Services, it was also extracted data from the Compustat from 31/12/1991 up until 31/12/2021, containing the CUSIP, return on equity, and the public date for US securities. A total of 1,749,518 companies' return on equity was obtained.

The two datasets were merged on CUSIP (an 8- or 9-digit unique stock identifier) and also by date, to obtain the final database containing the analyst's recommendation, the Return on Equity, by date, and CUSIP. The key "GVKEY" was added to this dataset for further analysis, leaving 341,353 observations on the portfolio after cleaning and filtering (to ensure that non-applicable or invalid values are filtered out).

In order to perform the strategy onwards, the returns from the US stocks were extracted from Compustat, covering data from January 2000 up until December 2020. This dataset was matched with the previously described dataset, covering the final factor. Concerning the risk-free data, in order to get the excess returns, data was taken out of Kenneth French Data Library. It is important to notice that the long-only and long-short strategies were constructed on a value-weighted basis based on each firm's market capitalization. Thus, bigger stocks with a bigger market cap will have a stronger weighting in the strategy. Also, to evaluate how the performance of the strategy is in different periods, the sample was divided into the first half (from January 2000 until December 2009), the second half (from January 2010 until December

2020), and of course, the full sample (covering the entire period, from January 2000 until December 2020).

Signal Construction

The main strategy focuses on the abnormal returns that may come from investing in stocks with a strong buy recommendation and a high return on equity. As it is shown by Jegadeesh (2004) in the "The Journal of Finance", "a strategy that buys the quintile of stocks with the highest recommendations and sells the quintiles of stocks with the lowest recommendations earns 2.3% over the next six months". Also, investing in companies with a higher return on equity might help investors distinguish between companies that are profit creators instead of profit burners. However, return on equity may have some drawbacks: it does not tell investors whether a company has excessive debt and is raising more of its funds through borrowing rather than issuing shares. Thus, the strategy was constructed as the sum of both factors, allowing one to only pick stocks with a high recommendation but also a high return on equity, eliminating possible biases.

The long-only strategy's main idea is to take a long position on those stocks that present a higher factor, whilst the long-short strategy is done by sorting stocks based on the sum of the analyst recommendation for that stock and period plus the return on equity published at that time, and then taking a long position on stocks in the top quintile (the "winners") and shorting stocks in the bottom quintile (the "losers").

However, after some research, some different opinions started to appear. Per se, a paper published by Ertimur, Muslu, and Zhang (2011) found that stocks with 'strong buy' recommendations tend to underperform in the future, which might lead to the failure of this strategy.

To understand if analysts tend to be biased or if stocks with a "strong buy" have a probability of underperforming and getting overvalued – this is, getting a price that is not expected given their earnings – and stocks with a “strong sell” get undervalued, a further analysis will be done by constructing a second strategy that does exactly the opposite of what analysts say while maintaining the return on equity rule. This means that this new strategy will buy stocks with a “strong sell” recommendation and high return on equity, and sell stocks with a “strong buy” recommendation and low return on equity. The rule on return on equity is kept the same so we can get a look at how consensus moves with the profitability concept, and how that affects the performance of the strategy.

Strategy Overview

The purpose of this section is to analyze the strategy's performance (long-only and long-short) and compares it to how different it would perform if any investor decided to go against what analysts recommend. To execute the analysis several performance measures were calculated, mainly the average annualized excess returns, the annualized Sharpe ratio, and also the information ratio.

Furthermore, to understand the excess strategy returns, the Capital Asset Pricing Model (CAPM) and the Fama-French Three-Factor Model (FF3) (Fama and French (1992)) regressions were performed to compute the alpha, its relevance, and also the information ratio. Whilst CAPM is a single-factor model based on the relation between returns and the market factor, FF3 is an extension of the capital asset pricing model, that adds three separate risk factors: market, size, and volatility.

From Table 1, one can see that both portfolios perform very differently throughout the entire sample. When looking at the long strategy, one can see that the full sample got an average annualized excess return of 7.11% with an annualized volatility of about 32%. Regarding the first and second halves the values are much different (while the first half got a negative average annualized excess return of -5.6%, the second half obtained the highest value, of 21.48%). As for the standard deviation, the first half was much more volatile (35.06%) versus the second half (28.8%). Looking at the Sharpe ratio, which is a measure of the risk-adjusted return of a financial portfolio, the second half got the highest Sharpe ratio (of 0.68) and the first half the worst Sharpe ratio (of -0.16), which is consistent with a much higher volatility and lower returns, leading to an overall Sharpe ratio of 0.21. The highest the Sharpe ratio, the more the investor can generate higher returns on a risk-adjusted basis.

The long-short strategy can generate lower risks but also lower returns. The full sample is only able to get an average annualized return of 1.46%, a volatility of 29%, and a Sharpe ratio of 0.05. The first half and second half of the sample both achieve a positive yet low annualized return (2.66% and 0.27%, respectively), a volatility that rounds 29% in both portfolios, and also a Sharpe ratio of 0.09 for the first half and 0.01 for the second half. Despite the long-only strategy having a better performance than the long-short strategy, overall it still presents the lowest returns given the risk.

Table 1 shows the results for the full sample period (in-sample) and for the first and second halves (out-of-sample) to test the consistency of the strategy in different portfolios.

Table 1: Performance statistics summary on IBES and profitability strategies

Strategy	Period	Annual Return	Volatility	Sharpe Ratio
Long-only	Full sample	7.11%	32.24%	0.21
	First half	-5.60%	35.06%	-0.16
	Second half	21.48%	28.80%	0.68
Long-short	Full sample	1.46%	28.88%	0.05
	First half	2.66%	28.77%	0.09
	Second half	0.27%	29.10%	0.01

As it is depicted in Figure 1, the long-only strategy hits its bottom early in the sample (beginning of 2000) but starts to slowly increase throughout the first decade, with a slight step back in 2008 (major world financial crisis). During the second half of the sample, it is clear that the returns ascent rapidly amid the Covid-19 pandemic, reaching approximately 150% cumulative returns. Despite starting higher than the long-only strategy and the market portfolio, the long-short strategy is not very stable throughout the sample, with lots of difficulties. Contrary to what happened in the long-only strategy, in the second half, the strategy performs worse, reaching its peak decline in 2020. The results in Figure 1 are consistent with the results from the naïve performance.

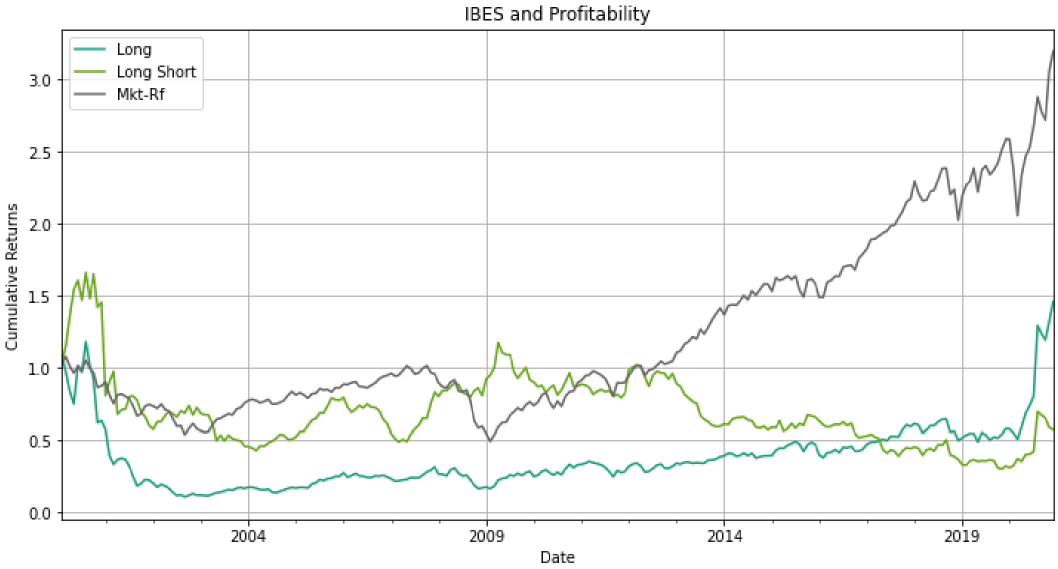

Figure 1- Cumulative returns of the IBES & profitability strategies

In what regards the analysis of the performance under the CAPM and the Fama-French Three Factor Model (FF3) both suggest that either the long-only or the long-short strategy has negative alphas and mainly insignificant exposure to this factor. Also, consistent with what we have seen before, the first half performs poorly that the second half only in the long-only strategy. In the long-whort strategy, the first half performs better.

The information ratio (IR) provides investors with insights about the ability of a fund manager to sustain the generation of excess, or even abnormal (or "abnormally high"), returns over time. The information ratio is similar to the Sharpe ratio, however, the first measures the risk-adjusted returns relative to a certain benchmark while the Sharpe ratio compares the risk-adjusted returns to the risk-free rate. The information ratio is calculated by dividing the corresponding alpha obtained from the CAPM or Fama-French model by the standard deviation of the residuals.

Looking at the results in Table 2, the information ratios suggest negative ratios for the whole sample period in the long-only strategy, which can be attributed to high volatility. The alpha, also always negative throughout the sample, in this strategy, refers to the excess returns earned on investment above the benchmark return. Given its negative performance, the long-only strategy seems to not be capable to outperform the market throughout the whole sample.

Table 2 shows the result of several performance measures of the long-only strategy.

Table 2: Results of the CAPM & FF3 regression on the long-only portfolio excess returns

Long-only	Full sample	First half	Second half
CAPM			
Alpha	-3.62%	-4.02%	-1.19%
t-statistic	-0.78	-0.59	-0.18
IR	-0.17	-0.18	-0.06
FF3			
Alpha	-3.32%	-0.27%	-6.10%
t-statistic	-0.8	-0.05	-0.94
IR	-0.18	-0.015	-0.32

By looking at Table 3, one can observe that the long-short strategy presents a positive alpha and information ratio in the full sample and during the first half, however, the second half has both these metrics negative. Therefore, it cannot be assumed that the strategy consistently out- or underperforms the market.

Table 3 shows the result of several performance measures of the Long-Short Strategy.

Table 3: Results of the CAPM & FF3 regression on the long-short portfolio excess returns

Long-short	Full sample	First half	Second half
CAPM			
Alpha	2.03%	2.28%	-3.50%
t-statistic	0.32	0.26	-0.37
IR	0.07	0.08	-0.12
FF3			
Alpha	2.86%	4.82%	-10.48%

t-statistic	0.45	0.54	-1.12
IR	0.1	0.18	-0.38

Given the overall negative results, I found it interesting to analyze a strategy that, as was said before, went against the consensus among analysts. Thus, a strategy whose factor is the sum of the reverse IBES recommendation plus the return on equity of the firm.

This analysis came from the skepticism around the consensus on analysts' recommendations brought up by previous research, which has shown that different researchers have somewhat different beliefs. Per se, Abarbanell and Bushee (1997) have stated that analysts' earnings forecasts do not fully efficiently incorporate financial statement information. Also, a study conducted by Bradshaw (2004) did not find any correlation between the consensus from analysts' recommendations and adjusted returns. Several prior studies even suggest an inverse relation between analysts' recommendations and future abnormal returns during certain periods.

All of this evidence suggests that analysts' consensus recommendations may not be informative—or worse, may be misleading.

First, in order to analyze and implement a new strategy it was necessary to adjust the data used in the previous strategy. The main idea was to not organize the IBES recommendation so that 1 means strong buy, 2 means buy, 3 means hold, 4 means sell, and 5 means strong sell. Afterward, it was added the return on equity to the 1-5 scale factor, and thus, this second strategy is based on sorting stocks into quintiles where the top quintile includes stocks with a strong sell recommendation and a high return on equity.

The same portfolios – long-only and long-short were created and both analyzed. To do so, the same performance measures were used, the annualized excess return, the volatility, and the Sharpe ratio.

When looking at Table 4, one can find that the excess returns and Sharpe ratio of the long-only are still higher than the long-short strategy, meaning that the long-only outperforms the long-short. However, both portfolios are above the strategy seen before. Despite the positive results that we can get from this naïve performance, the strategy maintains an extremely high volatility. In the long-only, the second half performs, once again, better than the first half. The opposite occurs with the long-short strategy (consistent with the first analyzed strategy).

Table 4: Performance statistics' summary on reverse IBES and profitability strategies

Strategy	Period	Annual Return	Volatility	Sharpe Ratio
Long-only	Full sample	10.49%	29.00%	0.34
	First half	2.80%	36.00%	0.08
	Second half	18.77%	21.00%	0.79
Long-short	Full sample	4.26%	27.00%	0.15
	First half	7.69%	26.80%	0.28
	Second half	0.90%	27.90%	0.03

By looking at the performance of the strategy in Figure 2, it is clear that the long-only portfolio almost mimicked the market, even though from 2018 onwards the strategy consistently outperforms the market, reaching more than 300% of cumulative returns.

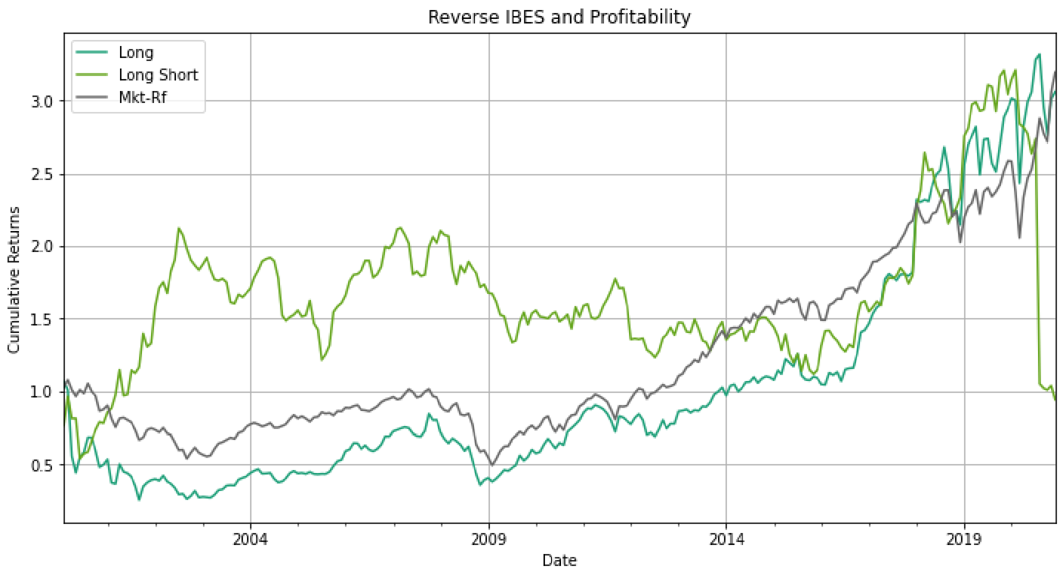

Figure 2 - Cumulative returns of the reverse IBES & Profitability Strategies

The long-short strategy has a really strong start at the beginning of the sample but ends up losing its power around 2012, slowly recovering but plunging to its lowest in early 2020 amid the Covid-19 pandemic and the financial consequences that came from it.

While analyzing the long-only performance under the CAPM and the Fama-French Three Factor Model, it is seen in Table 5, that the alpha is positive in both models almost throughout the whole sample (except in the FF3 Model during the second half). This is, the strategy can beat the market given that it manages to post stronger returns than comparable investments in the market. This is one of the major differences between the two strategies. As seen before, when following the analysts' consensus, the performance shows that is not able to outperform. In table 5, it is possible to observe the reported values for the long-only strategy.

Table 5: Results of the CAPM & FF3 regression on long-only portfolio excess returns

Long-only	Full sample	First half	Second half
CAPM			
Alpha	0.75%	4.38%	0.33%
t-statistic	0.16	0.55	0.07
IR	0.04	0.17	0.02
FF3			
Alpha	0.76%	7.63%	-0.71%
t-statistic	0.18	1.09	-0.15
IR	0.04	0.352	-0.05

As for the long-short strategy, the same can be stated. It presents positive and insignificant alphas. Also, under the Fama-French Three Factor Model, it presents an information ratio of 0.40 for the first half, which accordingly to most investors can be considered a good investment. In fact, it is the only period where the Information Ratio can get to the 0.40-0.60 interval.

Table 6 presents the summarized performance measures for the long-short strategy.

Table 6: Results of the CAPM & FF3 regression on long-only portfolio excess returns

Long short	**Full sample**	**First half**	**Second half**
CAPM			
Alpha	5.61%	7.18%	3.43%
t-statistic	0.94	0.87	0.38
IR	0.21	0.27	0.12
FF3			
Alpha	6.12%	9.89%	6.59%
t-statistic	1.07	1.26	0.73
IR	0.24	0.41	0.24

To sum up, several analyses were performed to understand which strategy would perform better. By following what the analysts recommend and focusing on highly profitable companies the long-only strategy can get 7.11% of excess returns, a volatility of more than 30% and is unable to beat the market. Throughout the sample, the information ratio is relatively low (reaching negative values). Thus, it is not a good strategy given the returns and the risk.

Whilst, by analyzing one strategy that buys stocks when there is a "strong sell" and vice-versa, the excess returns reach almost 11%. The volatility is still around 30% (which is extremely high) but the alphas are positive which can indicate that the strategy can beat the market, despite the high risk.

This paper shows a different approach to the analysts' recommendations, given that it might not be enough a "strong buy" mark, the stock also has to have a reasonable return on equity to be bought. But the question that appears is why following what the analysts recommend seems to generate lower returns than doing the opposite.

First of all, many investors believe that the success behind investing is in research, thus, many of them decide to blindly follow the analysts' opinions rather than doing their research. Also, many analysts do not predict out of pure joy, they can be biased. Many analysts often work for mutual funds, hedge funds, and brokerages, thus it can give the analyst a personal stake in forming a positive opinion about a stock that's in the best interest of the fund's portfolio, and not always an unbiased picture of what to expect from the stock. This might lead to many "buys" recommendations of a certain stock that ends up presenting worse results than expected. Investors buy an overvalued stock that culminates in underperforming the market. The opposite can happen with a "sell" stock.

Conclusion

This paper seeks to understand the performance of two strategies. The first one is constructed by following the IBES recommendations (consensus among investors) and also companies with a high return on equity, meaning highly profitable companies. The results show that this strategy does not present high annualized returns or low volatility. Given that, a strategy based on the opposite was created. This is a strategy that shorts stocks with a buy recommendation and low return on equity and takes long positions on stocks with sell recommendations and high return on equity.

Results show that a strategy on IBES and profitability are only able to achieve 7.11% of annualized excess returns, 32% volatility, and a Sharpe ratio of 0.21 with a long-only strategy, with the long-short strategy achieving an even lower return of 1.46%, volatility of 29% and a Sharpe ratio of 0.05. As for the reverse IBES and profitability, it is able to reach an annualized excess return of 10.49%, a volatility of 29%, and a Sharpe ratio of 0.34, with long-only performance. The long-short strategy fails to outperform the long-only strategy, with an annualized excess return of 4.26%, volatility of 27%, and a Sharpe ratio of 0.15. Despite the greater results and a good annualized excess return, this strategy is still highly volatile, so mixing it with other assets and diversifying the portfolio could work.

In conclusion, the long-only reverse IBES and profitability have the highest risk-adjusted performance. This might mean that analysts tend to be biased or even misleading when providing investors with their recommendations, so traditional investors or hedge funds might need to be cautious when following analysts.

Introduction

Quantitative investing dates back to 1950 but it was not until the late 1970s that it became popular. Today, sophisticated algorithm-based programs process billions of financial data in search of signals that a stock is likely to outperform the market. As the race between traditional and quantitative investment continues, hedge funds and investors are seeking to find new ways of delivering abnormal returns. This project aims to combine three previously created quantitative investment strategies: the value-weighted long-only IBES and Profitability, the value-weighted long-only cyclically adjusted EV-to-EBIT, and, lastly, the value-weighted long-short Intangible-to-Asset Growth. All three strategies are explained in more detail in the next section. The individual strategies were combined into three different portfolios: the equal-weighted portfolio, the tangency portfolio, and the global minimum variance portfolio. The purpose of this analysis is to see to which extent these diversified portfolios perform better than the individual strategies alone. This means, analyzing if each portfolio provides investors with superior risk-adjusted returns. The goal of building such portfolios is to combine various stocks by allocating them while minimizing risk and optimizing returns. Therefore, the tangency and global minimum variance portfolios are constructed in a way such that it automatically allows investors to readjust the individual strategies' weights throughout time in order to comply with the underlying strategy. The analysis is reported as follows. Section 3.1 presents a brief comparison between the individual strategies through some performance metrics. Section 3.2 describes the methodology behind the construction of the three portfolios. Further sections examine the naïve performance of all these portfolios and present the regression analysis using Fama French 3-Factor Model and Fama French 5-Factor Model. The final sections evaluate the portfolio weights and drawdowns over time, and lastly, compare our performance against a 60/40 portfolio.

1 Individual Strategies

2.1 Analyzing the Analysts: How does consensus moves with profitability?

2.1.1 Economic Motivation

These days, most of the investment community has adopted several quantitative strategies – machine learning, advanced mathematical models, factor investing, and many others– to outperform stocks and increase their returns when compared to an index. The purpose of this work project is to build and analyze a quantitative investment strategy based on both the Institutional Brokers' Estimate System (IBES) estimates and one of the measures of a company's profitability, the Return on Equity (ROE).

Prior studies by Womack (1996) found that an upgrade (downgrade) in a recommendation is associated with positive (negative) abnormal returns around their announcements. In addition, a paper published by the University of Illinois ("A Comparative Analysis of ROE and Value-to-Price based Trading Rules: Do Conventional Risk Factors Matter?") (2001), found that a ROE based trading rule could generate significant returns over 12 month period after portfolio formation.

2.1.2 Data and Methodology

Firstly, data was retrieved from IBES, covering quarterly US data from 01/12/1992 up to 31/09/2022, and containing the I/B/E/S Recommendation Code (IRECCD). IBES standardizes recommendations as 1 (strong buy), 2 (buy), 3(hold), 4 (sell), and 5 (strong sell). The order was reversed so that small numbers represent negative recommendations and higher numbers represent positive recommendations. Data from the Compustat covering 31/01/1991 until 31/12/2021 was also extracted, containing the return on equity for US securities. The two datasets were merged on CUSIP (an 8- or 9-digit unique stock identifier operated and maintained by the S&P Global Market Intelligence) and also by date, to obtain the final database containing the analyst's recommendation and the Return on Equity, by date, and CUSIP. To this dataset was added the key “GVKEY” for further analysis, leaving 341,353 observations on the portfolio after cleaning and filtering (to ensure that non-numerical or invalid values are filtered out).

The strategy was thus constructed as the sum of both factors and on a value-weighted basis. The long-only strategy’s main idea is to take a long position on those stocks that present a higher factor. This is, buying stocks in the top quintile (the “winners”) and selling stocks in the bottom quintile (the “losers”).

2.1.3 Performance Analysis

The purpose of this section is to analyze the strategy's performance (long-only and long-short) and compare how different it would perform if any investor decided to go against what analysts recommend. To execute the analysis several performance measures were calculated, mainly the average excess returns, the annualized Sharpe ratio, and also the information ratio.

Table 2: Performance statistics summary on IBES and Profitability strategies

Strategy	Period	Annual Return	Volatility	Sharpe Ratio
Long-only	Full sample	7.11%	32.24%	0.21
	First half	-5.60%	35.06%	-0.16
	Second half	21.48%	28.80%	0.68
Long-short	Full sample	1.46%	28.88%	0.05
	First half	2.66%	28.77%	0.09
	Second half	0.27%	29.10%	0.01

Table 1 shows the results for the full sample period (in-sample) and for the first and second half (out-of-sample) to test the consistency of the strategy in different portfolios. Overall, the long-only strategy presents a better performance after adjusting to risk, with a Sharpe ratio of 0.21, an annualized return of 7.11%, and volatility of more than 30%. Figure 1 shows how the long-only strategy hits its bottom early in the sample (beginning of 2000) but starts to slowly increase throughout the first decade, with a slight step back in 2008. During the second half of the sample, it is clear that the returns ascent rapidly amid the Covid-19 pandemic.

The long-short strategy is able to generate lower risks but also lower returns. The full sample is only able to get an average annualized return of 1.46%, a volatility of 29%, and a Sharpe ratio of only 0.05.

Despite starting higher than the long-only strategy and the market portfolio, this strategy is not very stable throughout the sample, with lots of ups and downs. Contrary to what happens in the long-only strategy, in the second half, the strategy performs worse, reaching its lowest point in 2020.

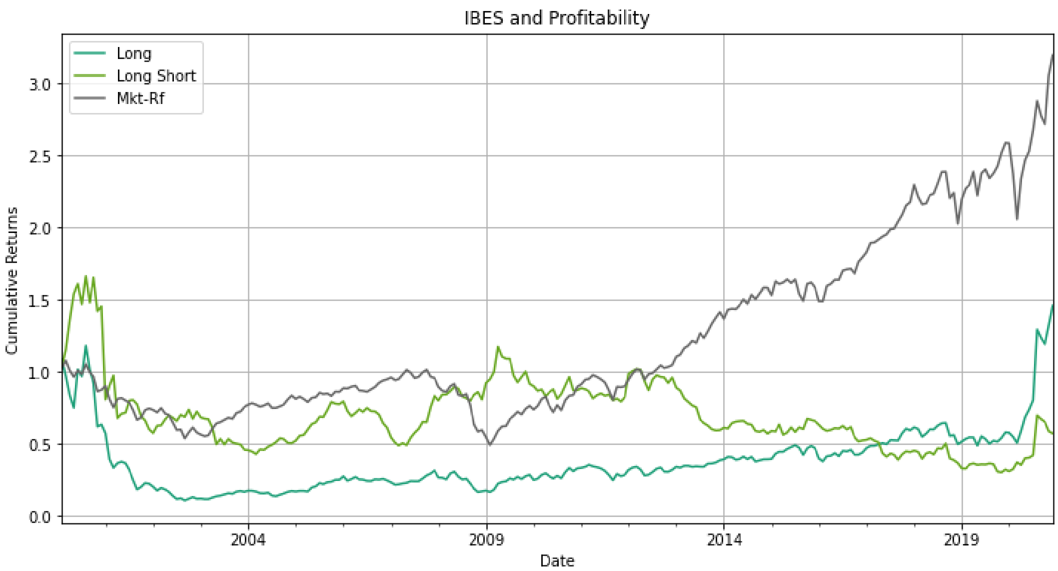

Figure 3: Cumulative returns of the IBES and Profitability strategies

However, after analyzing a strategy that goes against analyst recommendations but keeps the rule on return on equity, this is, that buys stocks with a “strong sell” recommendation and sells stocks with a “strong buy” recommendation, the results were curious.

This analysis came from the skepticism around the consensus on analyst’s recommendations that were brought up by previous research, that have shown that different researchers have somewhat different beliefs. Per se, Abarbanell and Bushee (1997) have stated that analysts’ earnings forecasts do not fully efficiently incorporate financial statement information. Also, a study conducted by Bradshaw (2004) did not find any correlation between the consensus from analysts’ recommendations and adjusted returns. And prior studies even suggest an inverse relation between analysts' recommendations and a future abnormal return during certain periods.

Table 3: Performance statistics' summary on reverse IBES and Profitability strategies

Strategy	Period	Annual Return	Volatility	Sharpe Ratio
Long-only	Full sample	10.49%	29.00%	0.34
	First half	2.80%	36.00%	0.08
	Second half	18.77%	21.00%	0.79
Long-short	Full sample	4.26%	27.00%	0.15
	First half	7.69%	26.80%	0.28
	Second half	0.90%	27.90%	0.03

The same performance measures as before were used to analyze this strategy. When looking at Table 2, one can find that the excess returns of the long-only are still higher than the long-short strategy, and also, both are above the strategy seen before. Despite the higher annualized returns, the strategy maintains extremely volatile (29%). By looking at the performance of the strategy in Figure 2, it is clear that the long-only strategy almost mimicked the market portfolio, even though from 2019 onwards it consistently outperforms the market, ending up with more than 300% of cumulative returns.

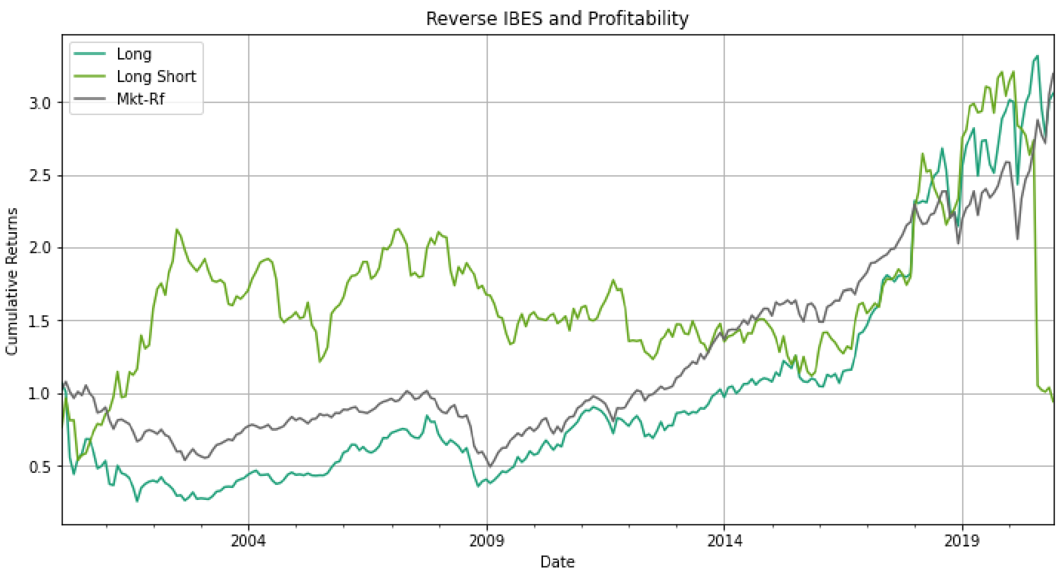

Figure 4 - Cumulative returns of the reverse IBES and Profitability strategies

While analyzing the long-only performance of this strategy under the CAPM and the Fama-French Three Factor Model, it is seen that the alpha is positive in both models almost throughout the whole sample, this is, the strategy is able to beat the market given that it manages to post stronger returns than comparable investments in the market. This is one of the major differences between the two strategies. As seen before, when following the analysts' consensus, the performance shows that is not able to outperform. As for the long-short strategy, the same can be stated. It presents positive and insignificant alphas. Table 3 presents the performance measures summarized for both strategies.

Table 4: Results of the FF3 regression on each portfolio's excess returns

Long-only	Full sample	First half	Second half
CAPM			
Alpha	0.75%	4.38%	0.33%
t-statistic	0.16	0.55	0.07
IR	0.04	0.17	0.02
FF3			
Alpha	0.76%	7.63%	-0.71%
t-statistic	0.18	1.09	-0.15
IR	0.04	0.352	-0.05
Long short	**Full sample**	**First half**	**Second half**
CAPM			
Alpha	5.61%	7.18%	3.43%
t-statistic	0.94	0.87	0.38
IR	0.21	0.27	0.12
FF3			
Alpha	6.12%	9.89%	6.59%
t-statistic	1.07	1.26	0.73
IR	0.24	0.41	0.24

Further analysis will be done on the reverse IBES and profitability strategy given its superior performance, presenting not only higher annualized returns (10.49% vs 7.11%), lower volatility (29% vs 32%), and also positive alphas throughout the sample. For simplification effects, this strategy onwards will be mentioned as "IBES and Profitability".

2.2 Exploiting value with a cyclically adjusted enterprise value-to-EBIT ratio

2.2.1 Economic Motivation

Among the several investment strategies that have been developed over time, value investing, first developed by Graham and Dodd (1934) is still highly above by modern investors, such as

Warren Buffet, one of the world's most successful investors. However, value investing has been controversial recently due to a sharp decline in returns in the second half of the 1963-2019 period, affirmed by Fama and French (2020).

Within the concept of value investing, there have been developed several systematic implementations of value portfolios, i.e., portfolios of stocks sorted on measures like price/earnings (P/E) or dividend yield (DIV/P). Shiller (1996) introduced the cyclically adjusted price-to-earnings ratio (CAPE), a variant of the P/E that divided the current price of a stock by its average inflation-adjusted earnings over the last ten years. The CAPE, also known as Shiller's ratio, still shows conceptual limitations similar to P/E. Among these is the fact that neither CAPE or P/E consider the company's debt, which can affect both the share price and the company's earnings.

Seen this, the main rationale of the investment strategy developed based on a cyclically adjusted enterprise value-to-EBIT ratio (CAEE) was to expand the CAPE ratio concept by attenuating one of its limitations: the disregard of each firm's debt. Moreover, it was intended to exploit value investing with CAEE to understand if value is in fact "dead".

2.2.2 Data and Methodology

The creation and further analysis of the strategy based on the cyclically adjusted EV-to-EBIT ratio has been carried out on the US stock market. To build the ratio, annual company fundamentals data has been downloaded from January 1991 until December 2020 from the Compustat database. More concretely, it was retrieved the common shares outstanding ($CSHO_{i,t}$) and the price close ($PRCC_{i,t}$) at year-end to compute the market value for each company ($MV_{i,t}$), and the total long-term debt ($DLTT_{i,t}$), the total debt in current liabilities ($DLC_{i,t}$), and cash and short-term investments ($CHE_{i,t}$) to calculate the net debt ($ND_{i,t}$), which were both necessary to calculate the enterprise value ($EV_{i,t}$) for each stock within the sample. To guarantee the reliability of the data, duplicates were removed, as well as stocks with common shares outstanding or price close equal to zero, as indicates that were not publicly traded at some point. Furthermore, the denominator of the ratio ($EBIT10_{i,t}$) was computed doing the simple moving average of the operating earnings for each firm stock ***i*** ($EBIT_{i,t}$) using a period of ten years (from ***t-9*** to ***t,*** included).

EBIT data has been filtered to values equal or higher than **ε** (*epilson*), being **ε** a real positive number that can be as small as necessary, to restrain the CAEE ratio (detailed in Equation 1) from outliers or non-sense values.

$$CAEE_{i,t} = \frac{EV_{i,t}}{EBIT10_{i,t}}$$

*Equation 1: The $CAEE_{i,t}$ ratio represents the $EV_{i,t}$ –to– $EBIT10_{i,t}$ relation for each stock **i** at time **t.***

Since the CAEE ratio can be sector biased, as stocks within capital intensive sectors, with typically lower EBIT values, that will systematically have a higher EV/EBIT, leading to higher CAEE values, it was taken the sector for each stock in the sample from Compustat (GSECTOR), which represents the first level in the hierarchy of the Global Industry Classification Standard (GICS), and created a standardized CAEE ratio (Equation 2).

$$SEC_{AVG_t} = \sum_{i=1}^{n} CAEE_{i,t} * \frac{MV_{i,t}}{Total\ MV_t} \tag{2.1}$$

$$STD\ CAEE_{i,t} = CAEE_{i,t} - SEC_{AVG_t} \tag{2.2}$$

Equation 2: The first formula represents the sector value-weighted CAEE average (SEC_{AVG_t}) at each point of time t, while the second describes the $STD\ CAEE_{i,t}$ ratio for each stock i at time t.

Long-only and long-short strategies were developed for the CAEE and the STD CAEE separately to compare both ratios' performance. To assess this, monthly value-weighted returns, with weights calculated at month ***t*** based on each firm's market capitalization at month ***t-1***, and equal-weighted returns were computed. The rationale of the equal-weights method was solely to test the impact of the weighting scheme on the strategies' performance. Then, monthly excess returns were calculated subtracting the risk-free rate at month ***t*** from both monthly value-weighted and equal-weighted returns. As the ratio was developed from the CAPE ratio, this was retrieved from Compustat and used as a benchmark after following the same procedure.

Based on the logical interpretation of the ratio, which is also applicable for the standardized one, it was expected that the lower the ratio, the higher the returns generated. Therefore, the long-only strategies were created by holding long the first tercile, and to create the long-short strategies it was added a short-leg to these that held short the third tercile. Although using monthly returns, all the strategies are rebalanced annually due to the use of annual fundamentals.

2.2.3 Performance Analysis

All the portfolios are firstly, compared through a naïve performance analysis considering the average annual excess returns, the standard deviations, and the respective Sharpe ratio statistics, which are summarized on Table 4.

Table 5: Performance statistics‘ summary on CAEE strategies

Weighting Scheme	Factor	Strategy	Annual Return	Volatility	Sharpe Ratio
Equal-Weights	CAEE	Long-only	15.96%	21.36%	0.75
		Long-short	4.51%	8.21%	0.55
	STD CAEE	Long-only	15.00%	21.19%	0.71
		Long-short	3.34%	6.52%	0.51
Value-Weights	CAEE	Long-only	10.30%	18.49%	0.56
		Long-short	3.70%	10.47%	0.35
	STD CAEE	Long-only	7.05%	17.32%	0.41
		Long-short	0.48%	7.09%	0.07
	CAPE	Long-only	4.72%	29.62%	0.16
	Market	Long-only	7.04%	16.33%	0.43

From Table 4, it is noticeable that the weighting scheme used to form the portfolios has a substantial impact on their performance. In the light of literature, Kevin Chiang (2002) proved that “equal-weight portfolio return metric systematically yields higher estimates of portfolio returns than value-weight portfolio return metric, as a result of the empirical negative correlation between within-sample value weights and raw returns distorting the true weights within the sample". Despite the lower volatility of the value-weight portfolios compared to the equal-weight ones, their Sharpe ratios are still lower, meaning that when using an equal-weighting scheme, the risk-adjusted performance is better. Overall, the long-only CAEE strategy is the one that shows better performance after adjusting to risk with Sharpe ratios of 0.76 and 0.56, using equal-weights and value-weights, respectively.

Following with the performance analysis, only the value-weighted portfolios were used for comparison with both the market and the benchmark (the CAPE based strategy), exhibited on Figure 3, as these are more realistic.

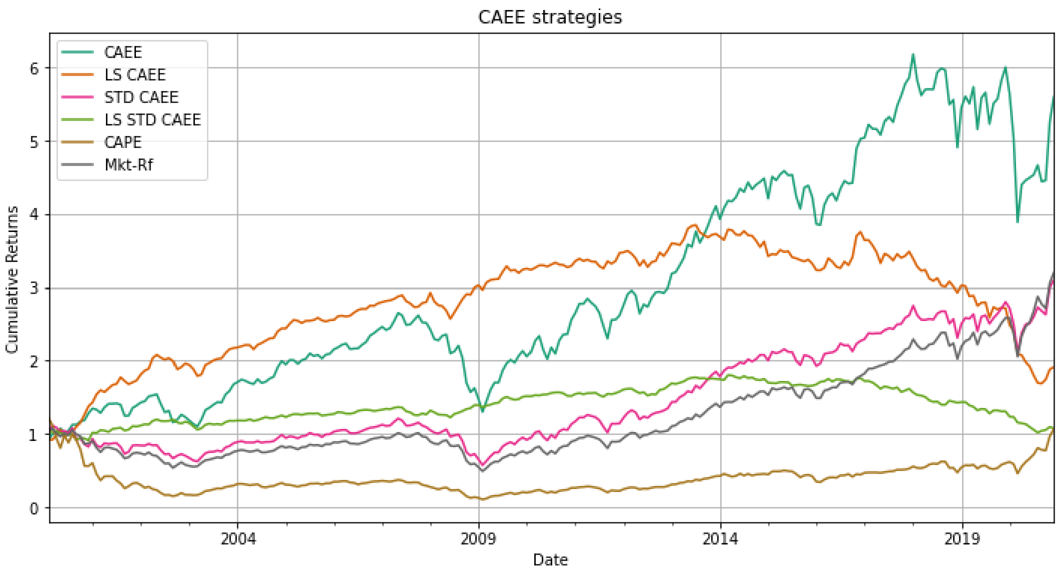

Figure 5: Cumulative returns of the value-weighted CAEE strategies against the market portfolio (Mkt-Rf), and the benchmark (CAPE)

The figure highlights the outperformance of the long-only CAEE strategy over all the other portfolios. On the one hand, the long-only outperformance over the long-short strategies suggests that firms with high CAEE did not present substantially lower returns than firms with low CAEE, so short-selling the first tercile led to lower cumulative returns on the long-short strategy compared to the short-constrained one. On the other hand, it is noteworthy that the long-short strategies are less volatile, uncorrelated with the market, and outperformed the respective long-only strategies until mid-2014, but significantly drown after, leading to lower cumulative returns by the end of 2020. The STD CAEE underperformance compared to the CAEE, both on the long-only and the long-short strategies, was a surprise, showing that removing the sector bias does not generate higher returns, but decreases the portfolio's volatility. All strategies significantly outperformed the benchmark, suggesting that using the CAPE ratio at the stock level may not be very effective on generating excess returns.

The naïve performance analysis omits the underlying risk factors that ultimately drive the returns of the investigated portfolios. Therefore, excess returns were tested considering the Fama French 3-factor model (FF3), and the results are summarized on Table 5.

Table 6: Results of the FF3 regression on each portfolio excess returns

Factor	Strategy	α	β_{MKT}	β_{HML}	β_{SMB}	t-stat	R^2	IR
CAEE	Long-only	2.67%	0.972	0.595	-0.019	2.154	0.900	0.48
CAEE	Long-short	0.23%	-0.025	0.685	0.143	1.770	0.546	0.39
STD CAEE	Long-only	-0.14%	0.997	0.127	0.012	-0.113	0.895	-0.03
STD CAEE	Long-short	-0.01%	0.001	0.217	0.174	-0.056	0.157	-0.01
CAPE	Long-only	-0.61%	1.505	-0.336	0.715	-3.887	0.915	-0.86

The results overall reinforce some of the conclusions stated on the naïve analysis. More concretely, the long-only CAEE strategy reinforced itself as the best performer with the higher abnormal rate of return, measured by alpha (2.67%), being statistically significant at a 95% confidence level, as the t-statistic is higher than 1.96. Moreover, it has a positive loading on the MKT and the HML factor, while negative on SMB, as expected, indicating that the portfolio returns are weighted towards value stocks, complying with the main objective of the strategy, and big-cap stocks. The R-squared is close to 1, meaning that the FF3 explains well the portfolio's returns, or in trader terms, it is a good hedge on the portfolio. Other than that, long-short strategies have a MKT factor loading close to zero, reinforcing their low systematic risk. Apart from the CAEE based strategies, the other portfolios have negative alphas. Regarding the

CAPE strategy, the negative factor loading on HML (-0.336) was a surprise, as it shows that the returns of CAPE strategy are mainly explained by growth rather than value stocks. Other than that, the information ratios overall reflect the t-statistics results, being greater than 0.40 in absolute terms for significant alphas, and lower for insignificant alphas.

2.3 Intangible-to-Asset Growth

2.3.1 Economic Motivation

The intangible-to-asset growth strategy aims to utilize recent development in the estimation of intangible assets, the increased importance of intangible assets, and the well-established asset growth effect (Cooper, Gulen, and Schill 2008). The intangible-to-asset growth ratio measures the relative growth in investments in intangible assets compared to the growth in total assets. The approach is mainly motivated by the work of (Eisfeldt, Kim, and Papanikolaou 2020), which shows how integrating intangibles into the book value of assets improves a classic value approach to investing. Since intangible assets such as intellectual property, customer relationships, brand recognition, and human capital are increasingly important in the modern economy they should not be overlooked as an explanatory factor for stock returns. However, it lies in the nature of intangible assets and in the accounting principles that govern their recognition that they are not easily quantifiable. Since internally developed intangible assets are most of the time expensed rather than capitalized, methods that accumulate certain expenses are often used to estimate the value of a firm's intangible capital stock. Other methods, like questionnaires, are not practical for the construction of a trading strategy since the data is often limited. This study is following the perpetual inventory method relying on Selling, General & Administrative expenses (Eisfeldt and Papanikolaou 2014) to estimate the stock of intangible assets on a quarterly basis. The intangible-to-asset growth factor is then calculated by dividing the growth of intangibles by the growth of total assets. This ratio should be able to capture how efficiently a company is spending its money. Since the asset growth effect shows that higher growth rates in total assets are linked to lower stock returns and lower growth rates are linked to higher stock returns, we assume it to be the other way around for intangible growth rates due to the enhancing effect on the value factor and the described increased importance of intangible assets. Hence, the hypothesis is that the higher the intangibles-to-asset growth ratio the more efficiently resources are spent. A low ratio suggests that the company is spending relatively too much on tangible assets in comparison to intangibles. A high ratio suggests that a company is developing intangible assets faster than tangible assets and should therefore be a predictor of more efficient utilization of capital. This strategy is insofar an extension of the approach by Cooper, Gulen, and Schill (2008) because it does not punish expanding companies with high growth in tangible assets if intangible assets grow by an equal or even higher proportion.

2.3.2 Data and Methodology

To construct the signals, we use quarterly company fundamental data obtained from Compustat via the Wharton Research Data base (WRDS). The return data is the same as for the two other strategies to have a common investment universe and obtained from the Center for Research in Security Prices (CRSP) as well as Compustat. The asset growth factor is constructed in the following way:

$$AssetGrowth_{it} = \frac{Assets_{it} - Assets_{it-1}}{Assets_{it-1}}$$

Equation 3: Asset Growth factor for stock i at time t.

This is the same approach as taken by Cooper, Gulen, and Schill (2008) with the slight difference that *t* is measured in quarterly intervals instead of annual intervals. To construct the intangible growth factor, first intangibles need to be estimated by following Eisfeldt, Kim, and Papanikolaou (2020) and applying the perpetual inventory method to flows of Selling, General, and Administrative (SG&A) expenses to compute INT_{it}.

$$INT_{it} = (1-\delta)INT_{it-1} + SG\&A_t$$

Equation 4: Perpetual Inventory Method to flows of SG&A for stock i at time t.

INT_{i0} is initialized by setting $INT_{i0} = SG\&A_t \,/\, (g + \delta)$ using SG&A when it first appears in Compustat. I set g to the growth rate of SG&A in my sample which is 0.189 and assume a depreciation rate of $\delta = 0.2$ following Eisfeldt and Papanikolaou (2014). I apply this method to all firms in Compustat and begin my main sample in 2000. Subsequently, I compute intangible growth on a quarterly basis for each firm:

$$INTGrowth_{it} = \frac{INT_{it} - INT_{it-1}}{INT_{it-1}}$$

Equation 5: Intangible Growth Factor for stock i at time t.

From this follows the newly introduced factor Intangible-to-Asset Growth (*IntAssetGrowth*), which is obtained by normalizing (min-max scaling) $INTGrowth_{it}$ and $AssetGrowth_{it}$ across companies for each point in time so that values fit into the [0,1] range. This is necessary to avoid negative growth values. Finally, the $IntAssetGrowth_{it}$ is constructed in the following way:

$$IntAssetGrowth_{it} = \frac{INTGrowth_{it}}{AssetGrowth_{it}}$$

Equation 6: Intangible-to-Asset Growth Factor for stock i at time t.

Portfolios are formed by sorting the stocks in the investment universe according to the signal in month *t* and dividing them into terciles. To avoid look-ahead bias the long (upper tercile) and long-short (long upper tercile, short lower tercile) portfolios are then applied to the returns in $t+1$. Portfolios are formed using market value weighting to ensure the feasibility of the strategy since large investments in small markets cap stocks potentially face liquidity constraints.

2.3.3 Performance Evaluation

Figure 4 shows the cumulative excess returns of the long and long-short Intangible-to-Asset growth strategy in comparison to the excess returns of a value-weighted portfolio of all the stocks in the investment universe (market portfolio). One can clearly see that the long and especially long-short strategies fail to outperform the market portfolio. The long-short strategy barely holds onto its starting value during the 20-year period. Furthermore, it is interesting that the long-short strategy showed a profit during the 2008 financial crisis and achieves rather low volatility. However, this should be taken with a grain of salt since it is not entirely clear if those positive aspects of the strategy are not simply caused by the short exposure to the market.

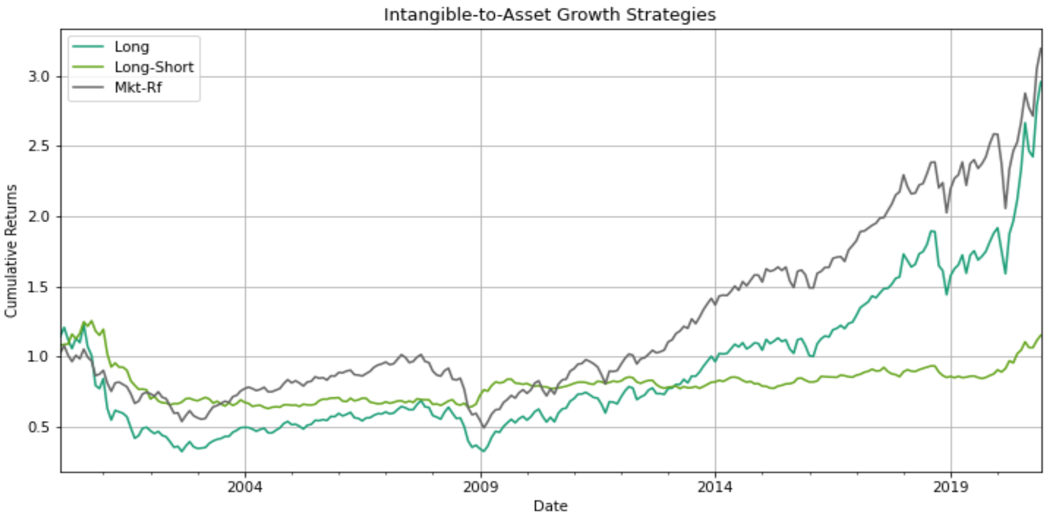

Figure 6: Cumulative returns of the Intangible-to-Asset Growth strategies

Table 6 shows the summary statistics for the strategy. Regarding the long-only strategy, we can note that although the arithmetic mean is around 0.8 percentage points higher than the arithmetic mean of the market strategy, it clearly falls short regarding its standard deviation and Sharpe ratio.

Table 7: Performance statistics' summary on Intangible-to-Asset Growth strategies

	Long-only	Long-short	Market
Average Excess Return	0.0760	0.0110	0.0683
Standard Deviation	0.2171	0.0921	0.1582
Sharpe Ratio	0.3500	0.1197	0.4315

Table 7 shows the Fama French 3-Factor analysis of the full strategy, the first half of the sample, and the second half of the sample. The long-only strategy is highly exposed to the market factor and negatively exposed to the HML factor, which means that the strategy tends to be exposed to stocks with low book-to-market ratios. The exposure to the SMB factor is for all subperiods close to zero and not significant. The long-short strategy behaves in a similar fashion regarding the exposure to the HML factor but exhibits a small but significant exposure to the SMB factor that is driven by the first half of the sample. The coefficient of the market factor is positive but small which suggests that the performance of the long-short strategy cannot be explained by the market risk factor.

Table 8: Results of the FF3 regression on each portfolio excess returns

	Full Sample Feb 2000 - Dec 2020		**First Half** Feb 2000 - July 2010		**Second Half** Aug 2010 - Dec 2020	
	Long	Long-short	Long	Long-short	Long	Long-short
Alpha	-0.0089	0.0040	0.0195	0.0220	-0.0191	-0.0037
	(-0.6168)	(0.2200)	(0.8389)	(0.6905)	(-1.0876)	(-0.1947)
Mkt - Rf	1.2761	0.1966	1.3280	0.1670	1.2264	0.2232
	(46.7689)	(5.7066)	(32.9222)	(3.0291)	(33.8264)	(5.6126)
HML	-0.3493	-0.2924	-0.3993	-0.3799	-0.2358	-0.2027
	(-9.4302)	(-6.2528)	(-7.3459)	(-5.1152)	(-4.4675)	(-3.5014)
SMB	0.0427	-0.1251	0.0498	-0.1891	-0.0642	-0.0471
	(1.0888)	(-2.5289)	(0.9314)	(-2.5880)	(-1.0201)	(-0.6822)
R^2	0.9113	0.2148	0.9136	0.2221	0.9169	0.2501
IR	-0.1369	0.0488	0.2704	0.2225	-0.3668	-0.0657

The table presents the results of a Fama-French 3 Factor Regression. T-statistics are in parentheses.

The explanatory power of the model, judged by the coefficient of determination, is very good for the long-only strategy but fails to explain the long-short strategy. However, the performance is rather poor for all strategies and all subperiods. The long-short strategy is proposed for the group portfolio since it offers a positive information ratio and might help to diversify the portfolio due to its low volatility.

2 Combined Strategy

The three strategies described above, and their corresponding returns were considered to create a combined strategy. Each strategy was treated as an individual security and further as part of a diversified portfolio, noting that each one only included equity. In the next subsections, the individual strategies first will be compared and then combined through three different procedures. Thus, three portfolios were created and further analyzed: the equal-weighted portfolio (EW), the tangency portfolio (TP), and the global minimum variance portfolio (GMV).

3.1 Comparison between individual strategies

The naïve performance metrics of each individual strategy, more concretely, the value-weighted long-only IBES and Profitability (S1), the value-weighted long-only cyclically adjusted EV-to-EBIT (S2), and the value-weighted long-short Intangible-to-Asset Growth (S3), are summarized on Table 8.

Table 9: Analysis of the average annual excess return, the volatility, and the Sharpe ratio for each individual strategy

	(S1) IBES and Profitability	(S2) Cyclically adjusted EV-to-EBIT	(S3) Intangible-to-Asset Growth
Annualized Return	10.49%	10.30%	1.10%
Volatility	29%	18.49%	9.21%
Sharpe Ratio	0.362	0.557	0.119

From Table 8, we can notice that S1, the IBES and Profitability strategy, shows the highest average annual return, followed by S2, the cyclically adjusted EV-to-EBIT strategy. However, S1 is highly volatile relative to the other strategies, and S2 is, thus, the best-performing strategy with the highest Sharpe ratio, showing the best risk-adjusted returns amongst the three individual strategies. S3, the Intangible-to-Asset growth strategy, showed the lowest annualized returns but carried less risk as well. Although the strategies do not proportionate incredibly high risk-adjusted returns individually, some interesting characteristics from each can make the combined portfolios more attractive.

a

Figure 7: Cumulative returns of the three individual strategies over the full sample

Figure 5, on the one hand, highlights the outperformance of the cyclically adjusted EV-to-EBIT strategy (S2) compared to IBES and Profitability (S1) and the Intangible-to-Asset Growth (S3) strategies. On the other hand, it shows that there is not much correlation between these, which is positive when merging the strategies into a combined portfolio, as it may reduce the overall portfolio's volatility. While S2 suffered a big drawdown in the first months of 2020, corresponding to the beginning of the Covid-19 pandemic, S3 maintained a very consistent position and did not suffer any significant decrease in cumulative returns. S1 returns, on the other hand, decreased similarly to S2, but at a smaller scale. However, during the dot-com bubble burst period (2000-2002), S1 was the strategy that consistently presented bigger drawdowns, but also higher peaks in returns, as Figure 6 reflects. Overall, Figure 6 reinforces the relatively high volatility of the IBES and Profitability strategy (S1), and, contrasting, the low volatility of the Intangible-to-Asset Growth strategy (S3).

Figure 8: Excess returns of the three individual strategies over the full sample

Although the previous charts do not show much correlation between the individual strategies at the first sight, a correlation matrix between their returns was computed to depict these analytically.

Table 10: Correlation matrix performed over the returns of the individual strategies

	S1	S2	S3
S1	1.00	0.52	0.25
S2	0.52	1.00	0.12
S3	0.25	0.12	1.00

From Table 9, it is noticeable that both S1 and S2 returns show a low correlation with S3 returns, 0.25 and 0.12, respectively. S1 and S2 returns present a higher correlation between them (0.52), but still significantly lower than 1. Therefore, it is possible to take advantage of the diversification effect (Markowitz 1959) within the combined portfolios.

3.2 Methodology

After comparing the individual strategies, the three combined portfolios mentioned above were constructed. The naïve combined strategy, which is the equal-weighted portfolio (EW), was constructed by assigning a weight of one-third to each individual strategy. The excess returns of this portfolio are, thus, described by the following equation:

$$r_t^e = {}^1\!/_3\, r_{S1,t}^e + {}^1\!/_3\, r_{S2,t}^e + {}^1\!/_3\, r_{S3,t}^e$$

Equation 7: Excess returns of the equal-weighted portfolio at time t.

Furthermore, an efficient frontier was built to find both the tangency portfolio and the global minimum variance portfolio (GMV). To find the tangency portfolio (TP), we computed the capital market line (CML), depicted in equation 8. This represents the allocation between the risk-free rate and the risky portfolio for all investors combined. An investor is only willing to accept a higher risk if the rate of return increases proportionally.

$$E(r_p) = r_f + \sigma_p \left[\frac{E(r_M) - r_f}{\sigma_M}\right]$$

Equation 8: Capital market line formula, where the slope corresponds to the market Sharpe ratio. When multiplied by the portfolio's volatility, it represents the risk premium.

The efficient frontier, which was developed by Markowitz in 1952, graphically represents all portfolios that maximize returns for each level of risk and is the upper part of the minimum-variance frontier. The last, in turn, maps all the feasible portfolios with different securities combinations.

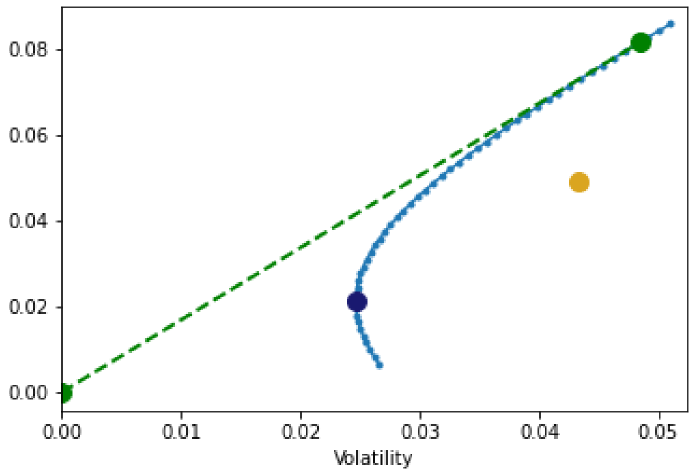

Figure 9: Graphical representation of the minimum variance frontier and the CML

From Figure 7, it is possible to find the global minimum variance portfolio (GMV), which is the blue point at the leftmost position on the minimum variance frontier, representing the portfolio with the lowest possible volatility. The efficient frontier, more concretely, is represented by the portfolios above the global minimum variance portfolio. All combinations below this point are not efficient, as there is always a portfolio that offers a higher expected return for the same amount of risk. Finally, the tangency portfolio (TP) is represented by the tangency point between the CML and the efficient frontier.

Since building a tangency portfolio and a global minimum variance portfolio based on the whole sample would result in a look-ahead bias, it is crucial to use an estimation window to compute expected returns, variances, and covariances. We settled for an estimation window of two years. This means that our sample now starts in February 2002 and uses the return data for the past two years to calculate the portfolio weights on a rolling basis.

3.3 Naïve Performance Analysis

We are then looking at three different types of portfolios: the equal-weighted portfolio (EW), also known as the 1/N rule, the tangency portfolio (TP), and the global minimum variance portfolio (GMV). The TP is the one with the highest return-to-risk combination measured by the Sharpe ratio, while the global minimum variance portfolio (GMV) minimizes the overall variance of the portfolio. Before the regression analysis, all portfolios were compared through a naïve performance analysis. To do so, we considered the average annual excess returns, the standard deviations, and the respective Sharpe ratio statistics for each portfolio, presented in Table 10.

Table 11: Performance statistics summary of the combined strategies

Portfolio	Annual Return	Volatility	Sharpe Ratio
Equal-weighted (EW)	7.01%	13.11%	0.53
Tangency portfolio (TP)	6.28%	15.39%	0.41
Global minimum variance (GMV)	3.29%	7.36%	0.45

From Table 10, one can see that different portfolios have somehow different performances. Whilst the global minimum variance portfolio (GMV) presents a lower annualized excess return (3.29%) and also a lower volatility (7.36%), the equal-weighted portfolio (EW) shows the highest annualized return of 7.01% and a volatility of 13.11%. Finally, the tangency portfolio (TP) shows the highest volatility but a lower annualized return of 6.28% compared to the EW portfolio. This analysis shows that the global minimum variance portfolio carries a lower risk than all the other portfolios, but also lower returns as they are correlated with volatility. By choosing the global minimum variance portfolio (GMV), investors are concerned with minimizing risks while also maximizing returns, so they diversify their holdings to reduce volatility such that no other portfolio produces a lower risk than the one at this point. The GMV portfolio however is unable to perform better than the TP. In fact, the latter is optimal because the slope of CML is the highest, meaning that we achieve the highest returns per additional unit of risk. However, this applies only to the estimation window. When applied to the next period, the GMV and the TP portfolios are both unable to outperform the EW portfolio throughout the whole sample. Also, despite the lower returns of the GMV portfolio, its Sharpe ratio (0.45) is higher than the tangency portfolio (0.41), while the equal-weighted portfolio reaches the highest risk-adjusted performance, with a Sharpe ratio of 0.53. Figure 8 highlights the outperformance of the equal-weighted portfolio over all the other portfolios. Taking into consideration an estimation window of 24 months – in order to eliminate the look-ahead bias – the equal-weighted portfolio has the highest cumulative returns, followed by the tangency portfolio and lastly, the global minimum variance portfolio. As for the fact that the equal-weighted portfolio outperforms the global minimum variance and the tangency portfolio from 2010 onwards should not come as a surprise given that many prior studies have shown the ability of the 1/N rule to outperform other portfolios. Nonetheless, the TP towered above all other portfolios from the beginning of 2002 until 2010. The three portfolios almost mimic one another, slowly increasing until late 2008 when the global financial crisis hit the economy and markets tumbled to their lowest values in years.

After that, all portfolios started to increase, with some pitfalls along the way but with the tangency portfolio getting around 350% cumulative returns, the equal-weighted portfolio more than 400%, and 200% for the global minimum variance portfolio.

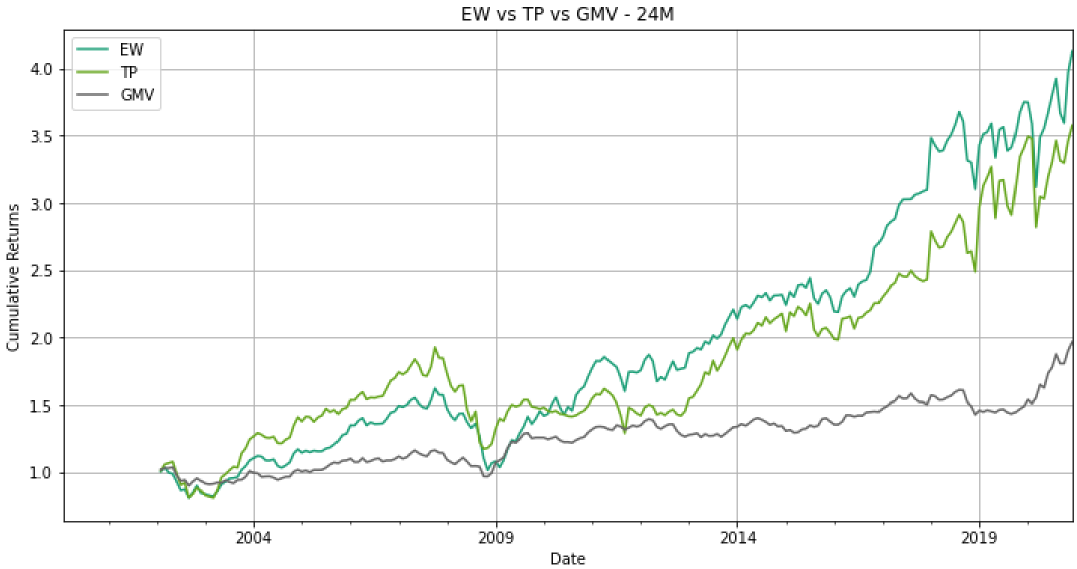

Figure 10: Cumulative returns of the three combined strategies

3.4 Fama French 3-Factor Analysis

Table 11 shows the results of a regression on the Fama French 3-factor model (FF3) (Fama and French 1992). The factors are obtained from Kenneth R. French's website[1]. We can observe that all three portfolios exhibit positive alphas between 2% and 3%, although only the alpha of the equal-weighted (EW) portfolio is statistically different from zero. Hence, only the EW portfolio shows an abnormal rate of return compared to the FF3 benchmark. Judging by the coefficient of determination we can see that the model differs in its ability to explain the performance of our three portfolios. The portfolio with the highest coefficient of determination is the EW portfolio. The exposure to the market is the highest in absolute terms and is highly significant. Additionally, the portfolio exhibits a significant value tilt.

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

Table 12: Results of the FF3 regression on each combined portfolio excess returns

	EW	TP	GMV
Alpha	0.0286	0.0300	0.0208
	(0.05)	(0.22)	(0.12)
Mkt-Rf	0.6498	0.6055	0.2421
	(0.00)	(0.00)	(0.00)
HML	0.1651	0.0305	-0.0633
	(0.00)	(0.63)	(0.06)
SMB	0.0401	0.0078	-0.0678
	(0.32)	(0.91)	(0.06)
R^2	0.7190	0.4310	0.2820
IR	0.4760	0.2723	0.3453

The table presents the results of a Fama French 3-Factor Regression. p-values are in parentheses. Alphas and Information Ratios are annualized.

The tangency portfolio is only significantly exposed to the market factor, although the exposure is smaller in magnitude compared to the equal-weighted portfolio's exposure. This is also true for the GMV portfolio at the five percent significance level. The GMV portfolio is the only one that has a negative value and size tilt, although small in magnitude and only statistically significant at the ten percent level. The information ratio (IR) reveals the superior performance of the EW portfolio compared to the two complex portfolios. It lies in an attractive range for investors with an IR against the FF3 benchmark of almost 0.5. This shows that rebalancing the portfolio with the goal of maximizing the Sharpe ratio or minimizing the variance can result in a worse performance than a simple 1/N portfolio weighting.

3.5 Fama French 5-Factor Analysis

To extend the analysis conducted in the previous section, we regress the excess portfolio returns on the Fama French 5-factor model in this section. The model was developed by Eugene Fama and Kenneth French in 2016 and is an extension of the famous 3-factor model. It proposes that the expected return of a stock can be predicted by five factors: market risk, size, value, profitability, and investment.

Table 13: Results of the FF5 regression on each combined portfolio excess returns

	EW	TP	GMV
Alpha	0.0159	0.0111	0.0092
	(0.30)	(0.67)	(0.50)
Mkt - Rf	0.6841	0.6602	0.2768
	(0.00)	(0.00)	(0.00)
HML	0.0658	-0.1179	-0.1389
	(0.20)	(0.17)	(0.00)
SMB	0.0916	0.0678	-0.0302
	(0.05)	(0.38)	(0.46)
RMW	0.1170	0.1563	0.1052
	(0.04)	(0.11)	(0.04)
CMA	0.1378	0.2563	0.1472
	(0.08)	(0.06)	(0.04)
R^2	0.7270	0.4450	0.3030
IR	0.2619	0.1009	0.1537

The table presents the results of a Fama-French 5 Factor Regression. p-values are in parentheses. Alphas and Information Ratios are annualized.

The additional factors profitability (RMW – robust minus weak) and investment (CMA – conservative minus aggressive) suggest that stocks with high operating profitability perform better and stocks of companies with high total asset growth have below-average returns, respectively. Both new criteria are examples of what is frequently referred to as quality factors. Table 12 presents the results of the regression on the 5-factor model. In comparison to the 3-factor model, we do not observe any statistically significant alphas. The abnormal risk-adjusted returns observed with respect to the 3-factor model for the EW portfolio are therefore explained by the added factors. All the portfolios show to some extent a profitability and investment tilt. The IRs drop below 0.3 for the EW portfolio and even below 0.2 for the more complex portfolios, which shows that by choosing the correct benchmark most abnormal returns can be explained by the exposure to risk factors.

3.6 Portfolio weights analysis

In order to better understand which individual strategies drive the portfolio performance, it is crucial to understand how the portfolio weights change over time. Figure 9 shows the evolution of those weights for the GMV and TP portfolios.

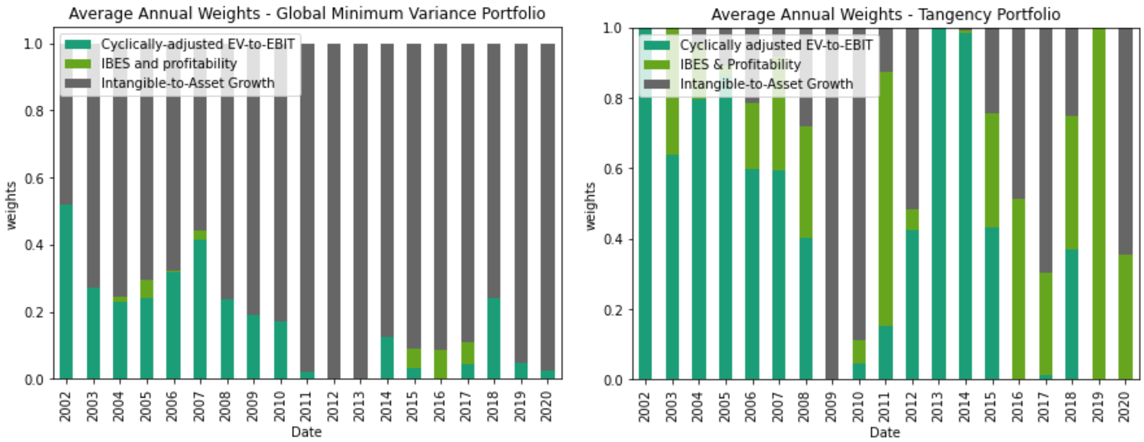

Figure 11: Average annual weights of the TP and GMV portfolio

We can see that the GMV portfolio is heavily dependent on the Intangible-to-Asset Growth strategy, which does not come as a surprise since it offers the lowest volatility of the three strategies. On the other hand, the IBES and profitability strategy only plays a minor role due to its high volatility. The tangency portfolio is heavily dominated by the cyclically adjusted EV-to-EBIT strategy, which is especially evident in the years leading up to the financial crisis of 2008. Interestingly, in 2009, the portfolio shifts completely to the Intangible-to-Asset Growth strategy, which mimics a minimum volatility approach. By looking again at Figure 8, we can see that this is in fact not good for the performance of the tangency portfolio in 2009 since it recovers slower than the EW and GMV approaches. During 2010, this reliance on the Intangible-to-Asset Growth strategy results in a loss in an overall favorable market environment. Hence, after the financial crisis, the TP adjusts too slowly back to the other two strategies. The weakness of the cyclically adjusted EV-to-EBIT strategy towards the end of the sample is also reflected in the TP, which relies from 2019 onwards entirely on the other two strategies. This shows that although the tangency portfolio has the problem to adjust quickly to rapidly changing market conditions it generally has the ability to switch to better-performing individual strategies.

3.7 Drawdown analysis

Figure 10 depicts the drawdown, which is the peak-to-trough decline of the portfolios. Hence, it is a measure of downside risk and gives the investor an idea of how long it takes to recover from a peak and what maximum loss historically occurred.

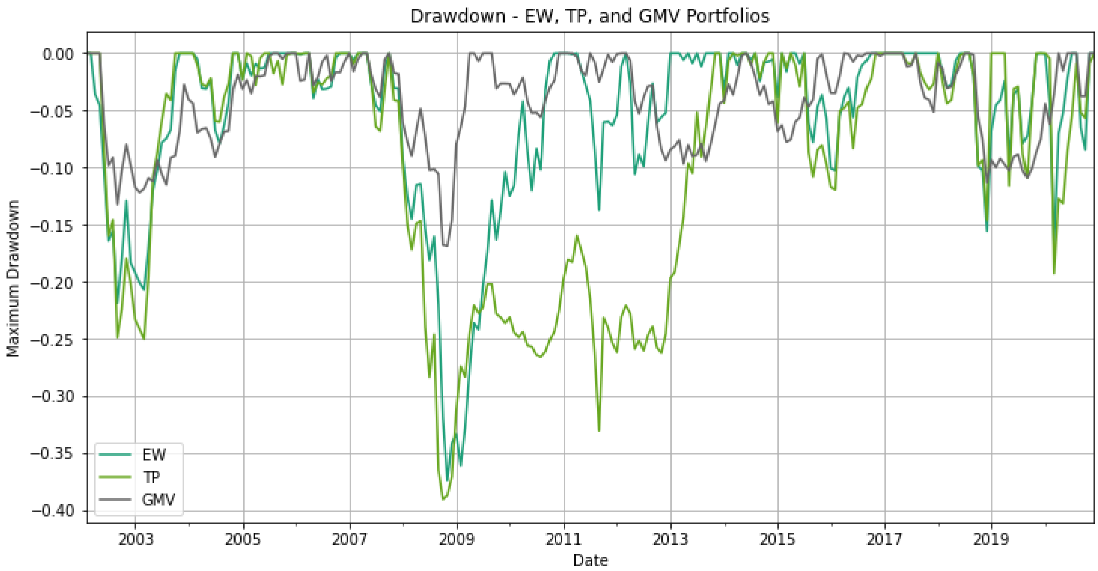

Figure 12: Drawdowns of the combined portfolios over the full sample

The GMV portfolio offers the lowest downside risk in terms of maximum drawdown, which shows that the strategy to minimize the portfolio variance effectively reduces downside risk. However, the portfolio that needs the least time to recover from its losses is the equal-weighted portfolio (Table 13). The tangency portfolio clearly performs the worst regarding the downside potential. Not only the portfolio loses almost 40% from its relatively highest peak to its relatively lowest trough but it also needs up to six years to recover. All things considered, the GMV portfolio offers the best protection against downside risk. It recovers almost as fast as the EW portfolio and exhibits a moderate maximum drawdown of about 17%.

Table 14: Drawdown analysis of each combined strategy

	EW	TP	GMV
Max. Drawdown	-37.46%	-39.12%	-16.87%
Max. Months in Drawdown	36	72	38

3.9 Investment strategies as part of a diversified portfolio

To further analyze the performance of our portfolios and investment strategies, we have added the iShares Core U.S. Aggregate Bond ETF (AGG) and the Vanguard Total Stock Market Index Fund ETF (VTI) to the portfolio formation process. They represent easily investible ETFs in the broad U.S. bond and stock market, respectively.

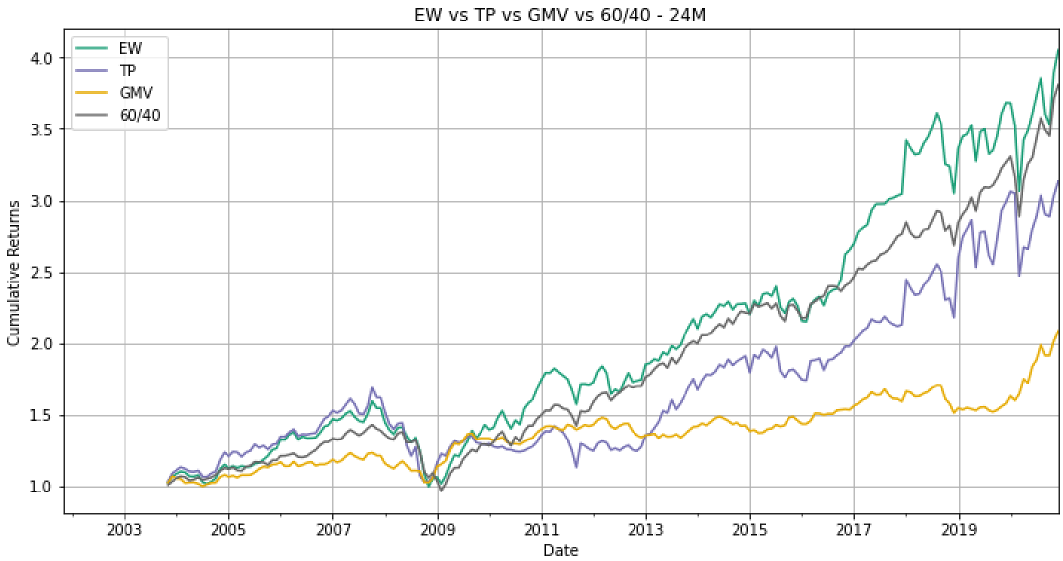

Figure 13 – EW, TP, and GMV against 60/40 portfolio

Figure 11 shows the cumulative returns of our three portfolios against a simple 60/40 portfolio, which invests 60 percent in stocks (VTI) and 40% in bonds (AGG). The beginning of the sample is set to the beginning of the AGG ETF sample period. Following the simple 60/40 rule leads to higher cumulative returns than our two complex strategies (TP and GMV) and only falls slightly short of the EW portfolio. However, the 60/40 portfolio exhibits lower volatility (0.09) than the EW portfolio (0.13). This shows that the complex method of building our three strategies, which possibly incurs high transaction costs, is not noticeably better than a simple 60/40 portfolio with monthly rebalancing.

Table 15: Average portfolio weights for Tangency Portfolio (TP) and Global Minimum Variance Portfolio (GMV) including AGG and VTI

	TP	GMV
Cyclically adjusted EV-to-EBIT (S1)	8.6%	5.7%
IBES and profitability (S2)	4.9%	0.8%
Intangible-to-Asset Growth (S3)	9.2%	19.4%
AGG	70.0%	73.9%
VTI	7.3%	0.2%

Table 14 shows the portfolio weights when we add the VTI and AGG ETFs to the portfolio optimization processes. Both portfolios are heavily dominated by bonds, which is caused by the sample period overlapping a period with extraordinary bond returns. Interestingly, S3 plays the biggest role of the three individual strategies. This is caused by low correlations to other investments and is likely a result of the short exposure of this strategy, since S1 and S2 are long-only strategies.

3 Conclusion

In conclusion, our research has shown that the combination of the individual strategies to a portfolio improves the performance in terms of risk-return considerations. We observe that the different return characteristics and risk exposures provide diversification benefits due to low correlations between the strategies, which is especially true for the Intangible-to-Asset growth strategy. Of the three implemented portfolios, the equal-weighted portfolio performs particularly well. This shows that investing according to more complicated strategies does not generally result in a better performance. The hope, that the tangency portfolio is able to timely switch its investments to the best-performing strategy, has not come true. Due to the estimation window of two years, the portfolio adapts too slowly to changing market environments. The Sharpe ratios of the individual strategies are not persistent enough that a tangency portfolio could provide better performance results than a simple 1/N portfolio. The global minimum variance portfolio achieves its goal – minimizing portfolio variance – relatively decent. For a defensive investor, the GMV portfolio could be attractive due to its relatively stable returns and ability to maintain its value during crises. However, it is heavily reliant on the Intangible-to-Asset growth strategy, which has very limited upward potential, slowly recovers from losses, and relies on a rather complicated security selection mechanism. Additionally, the annualized return of about 3.3% is only attractive in a low-interest rate and low-inflation environment. Finally, we can say that the cyclically adjusted EV-to-EBIT and Intangible-to-Asset Growth strategies offer some diversification benefits and could potentially improve a broad portfolio. The IBES and Profitability strategy however offers little diversification benefits due to its high volatility. Hence, we have not found a "get rich quick" scheme, it is hard to consistently outperform the market, and high returns are most of the time only earned by taking high risks.

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