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

FIELD LAB: ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

Analyzing the Analysts: How does consensus moves with profitability?

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

Intangible to Asset Growth and the Cross-Section of Returns

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Abstract

The group report aims to combine three strategies covering US equities: the IBES and Profitability, the cyclically adjusted EV-to-EBIT, and the Intangible-to-Asset Growth strategies. These were treated as individual securities to further create the equal-weighted, the tangency, and the global minimum variance portfolios. The first showed the best performance yielding on average 7.01% yearly, outperforming the market with a Sharpe ratio of 0.53 (vs. 0.43). The global minimum variance portfolio minimized indeed the volatility, which was significantly lower than the market's (7.36% vs. 16.3%). The three combined strategies performed worse than the best individual strategy – the long cyclically adjusted EV-to-EBIT.

Keywords: Finance, Financial Markets, US Stock Market, Performance Analysis, Modern Portfolio Theory, Portfolio Construction.

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1 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.

2 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 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

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.

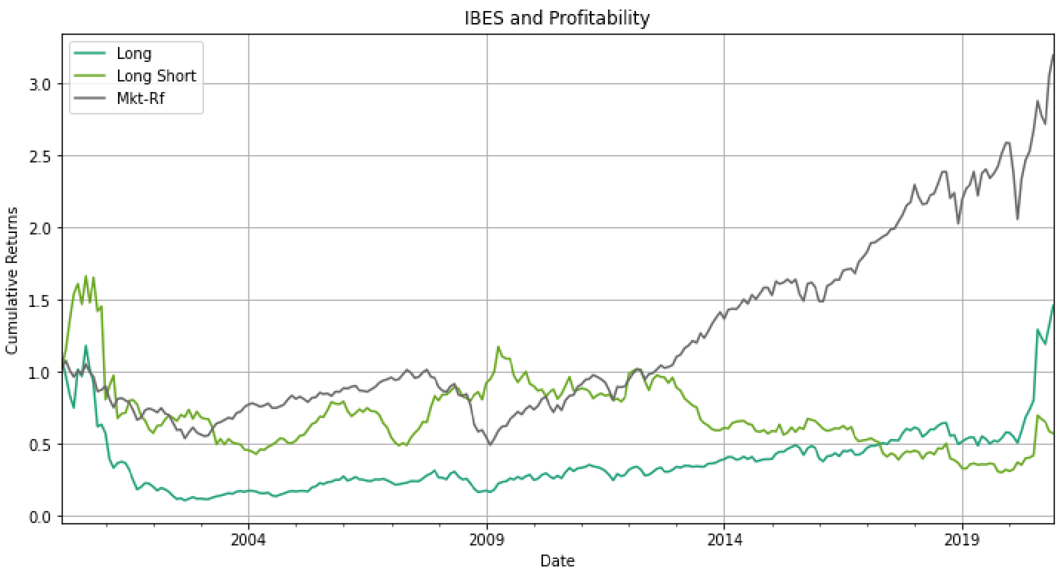

Figure 1: Cumulative returns of the IBES and Profitability strategies

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 2: 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.

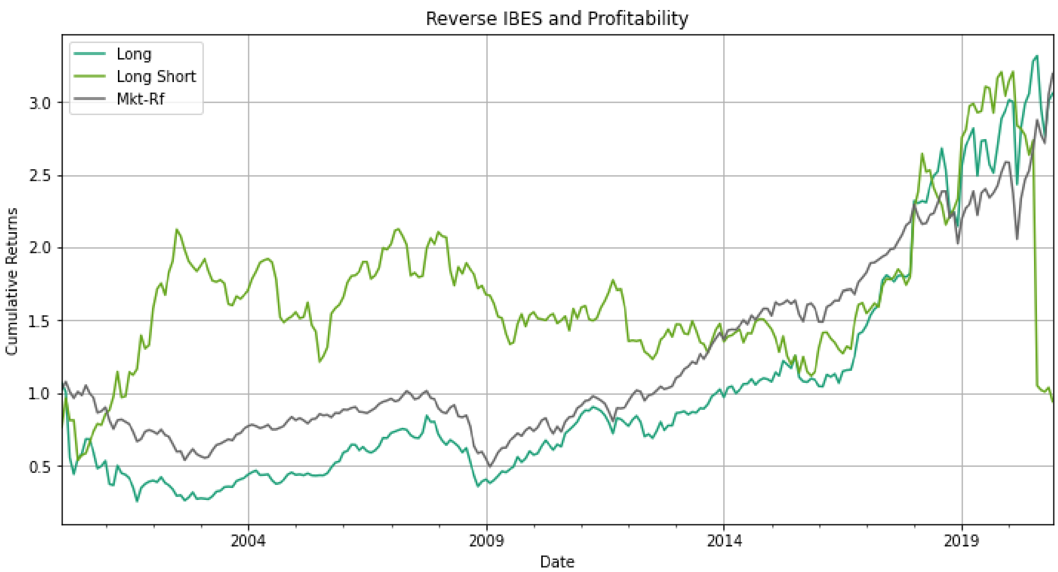

Figure 2 - Cumulative returns of the reverse IBES and Profitability strategies

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 3: 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 4: 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.

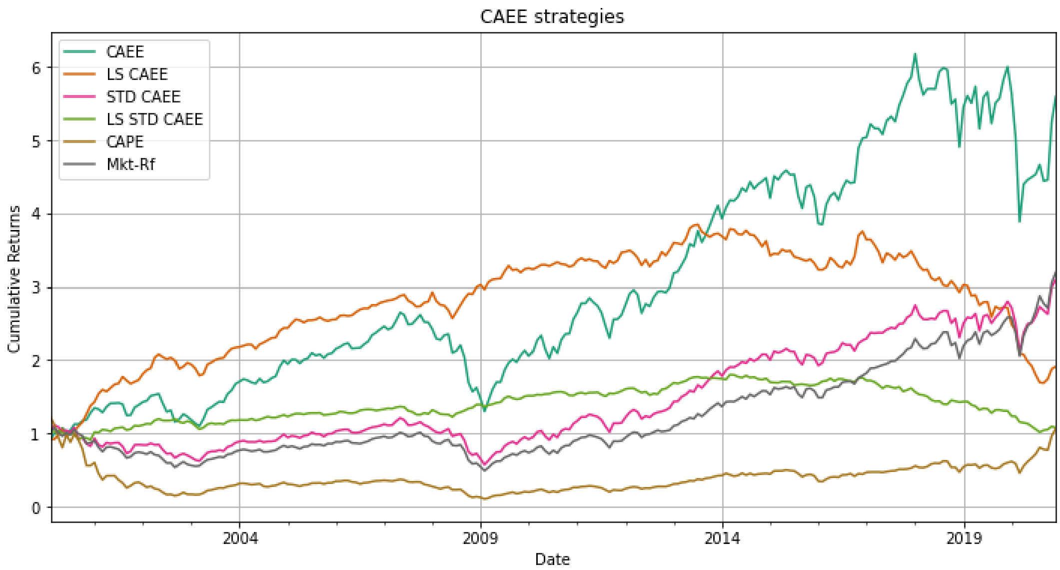

Figure 3: Cumulative returns of the value-weighted CAEE strategies against the market portfolio (Mkt-Rf), and the benchmark (CAPE)

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 5: 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.

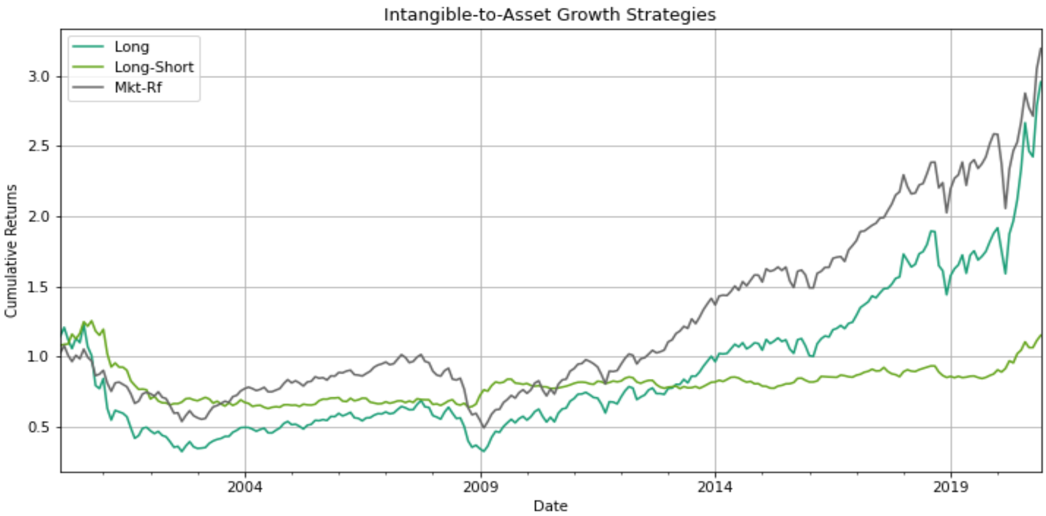

Figure 4: Cumulative returns of the Intangible-to-Asset Growth strategies

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 6: 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 7: 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.

3 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 8: 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.

Figure 5: 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 6: 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 9: 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.

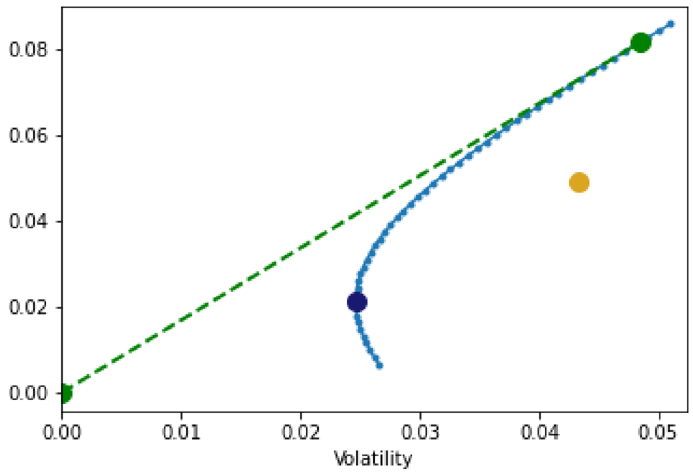

Figure 7: Graphical representation of the minimum variance frontier and the CML

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 10: 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 8: 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 11: 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 12: 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.

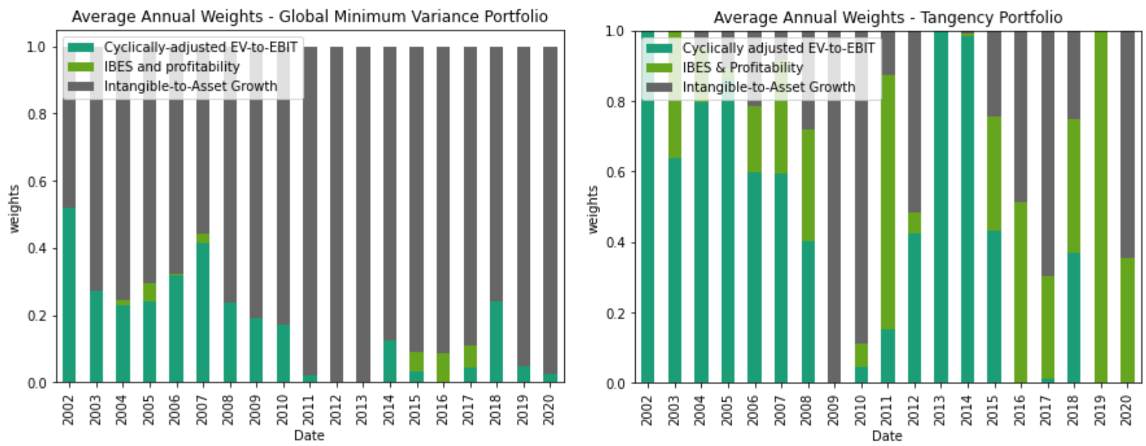

Figure 9: Average annual weights of the TP and GMV portfolio

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.

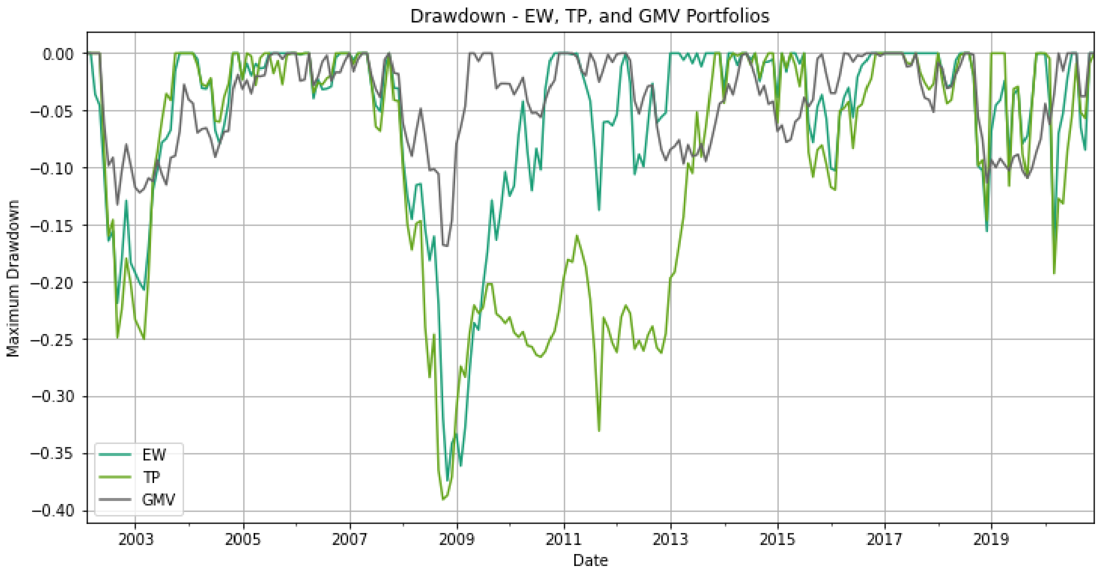

Figure 10: Drawdowns of the combined portfolios over the full sample

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 13: 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.

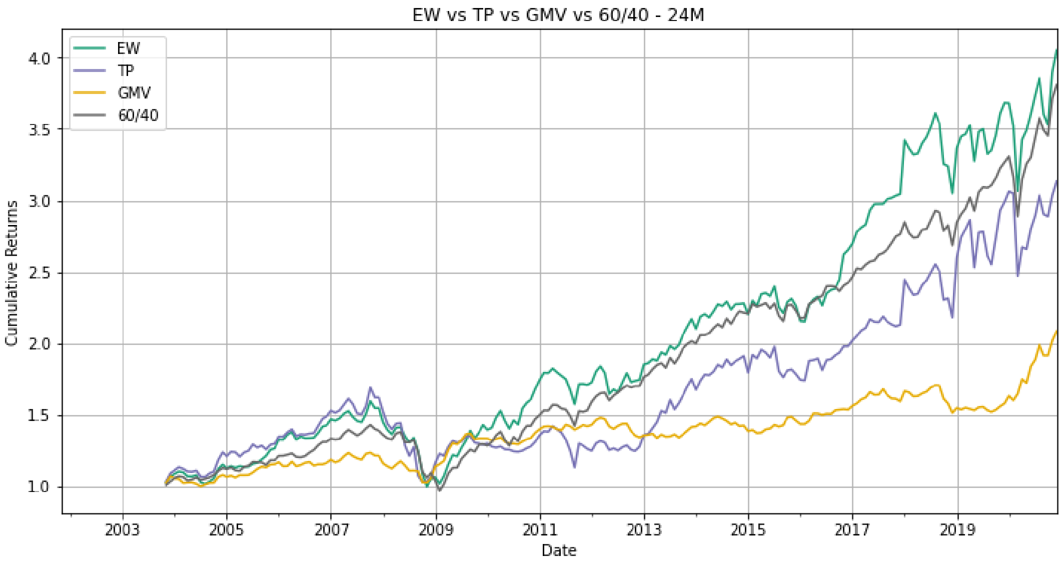

Figure 11 – EW, TP, and GMV against 60/40 portfolio

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 14: 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.

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

INTANGIBLE TO ASSET GROWTH AND THE CROSS-SECTION OF RETURNS

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Work project carried out under the supervision of:

Nicholas Hirschey

16/12/2022

Abstract:

Intangible assets are despite their increasing importance often omitted in factor investing approaches. I propose an extension to the asset growth factor (Cooper, Gulen, and Schill 2008) by building the intangible-to-asset growth factor based on quarterly fundamental data. Intangible assets are estimated based on a perpetual inventory method to flows of selling, general, and administrative expenses (Eisfeldt and Papanikolaou 2014). I show that long, and long-short portfolios build according to the intangible-to-asset growth factor underperform the market benchmark. Only the long-short strategy exhibits some diversification potential for a portfolio due to its low volatility.

Keywords:

Financial Markets, US Stock Market, Performance Analysis, Modern Portfolio Theory, Portfolio Construction, Intangible Assets, Asset Growth.

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1. Introduction

The main objective of this thesis is to build a quantitative investment strategy based on a newly developed ratio of intangibles to asset growth. The aim is to build upon the well-documented asset growth effect (Cooper, Gulen, and Schill 2008) and build a ratio that measures the relative growth in investment in intangible assets compared to the growth in total assets. Intangible assets such as intellectual property, customer relationships, brand recognition, and human capital are increasingly important in the modern economy. Companies are investing more in intangible assets such as software and research and development, as well as intangible assets related to customer experience, branding, and employee training. As technology advances and the economy shifts, intangible assets will become even more important in driving economic growth. Hence, it is likely that intangibles and intangible growth rates will play an increased importance in predicting future stock returns. Eisfeldt et al. (2020) already showed that a value approach to investing can be improved by incorporating intangibles into the book value of the ratio. I am following the perpetual inventory method relying on Selling, General & Administrative expenses (Eisfeldt and Papanikolaou 2013) to estimate the stock of intangible assets. Intangibles need to be estimated since internally developed intangibles are not recognized on the balance sheet. They are often expensed rather than capitalized due to the accounting principles that govern their recognition. I then calculate the quarterly growth in intangibles and calculate the ratio of intangibles growth to asset growth for that quarter. 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, I 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 et al. (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. The remainder of the paper is organized as follows. In section two, I review the literature on intangibles and empire building, in section three I briefly discuss the data, in section four I explain how the signal is constructed and in section five I present the results, possible explanations for the performance, and shortcomings of the strategy. Finally, I conclude the topic in section six.

2. Literature Review

As mentioned in the introduction this thesis aims to construct a trading signal based on recent developments in two different areas of financial research – the asset growth effect and improvements in the measurement of intangibles. Hence, I am going to review separately the asset growth and intangibles literature.

2.2 Asset Growth Effect

Cooper et al. (2008) showed in their widely cited paper that total asset growth, measured using the year-on-year percentage change in total assets over the 1968 to 2003 period, is highly negatively correlated with the cross-section of asset stock returns. Their research suggests that corporate events linked to asset contraction—such as spinoffs, share repurchases, debt prepayments, and dividend initiations—tend to be followed by periods of abnormally high returns, while events linked to asset expansion—such as acquisitions, public equity offerings, public debt offerings, and bank loan initiations—tend to be followed by periods of abnormally low returns. Preceding studies have shown the effects of components of a company's asset financing and investment. Fairfield et al. (2003) find that growth in net operating assets is negatively associated with one-year-ahead returns on assets. Richardson and Sloan (2003) show the negative relation between net external financing and future stock returns and Pontiff and Woodgate (2008) show that seasoned equity offerings, repurchases, and merger effects reflect negative abnormal returns. The main achievement of Cooper et al. (2008) is that they showed that the above-mentioned effects can be summarized under growth in total assets. Studies that follow can confirm the asset growth effect. Lipson et al. (2011) show that the effect is greater among stocks with higher arbitrage costs, while Titman et al. (2013) find that substantial differences exist across countries and the effect is more pronounced in countries with developed financial markets. Furthermore, they conclude that the effect does not seem to be associated with corporate governance or the costs of trading. Watanabe et al. (2013) provide evidence for the asset growth effect in international markets since studies conducted before only looked at U.S. equity returns. Moreover, they emphasize that it is more plausible that an optimal investment effect, as opposed to overinvestment, market timing, or other types of mispricing, is responsible for the observed cross-sectional relationship between asset growth and stock returns. Summarizing above mentioned studies, we can conclude that the asset growth effect is persistent over many studies, timeframes, and holds ups internationally.

2.3 Intangibles

Eisfeldt et al. (2020) showed in a remarkable paper that the value approach developed by Fama and French (1992, 1993) can be improved by incorporating intangibles into the book value of assets. They argue that a main contributor to value's poor performance during the last decade is the deteriorating quality of book assets as a fundamental anchor due to the omission of intangible assets. Intangibles have become an increasingly more important part of a firm's capital stocks due to the increasing prevalence of digital and knowledge-based economies, the growth of the global marketplace, and the need for companies to differentiate themselves in increasingly competitive industries. Corrado et al. (2009) estimated intangibles to be about one-third of the US non-residential capital stock in 2003. More recently, Eisfeldt and Papanikolaou (2013), Falato et al. (2022), Belo et al. (2022), and Ewens et al. (2019) estimate the contribution to be around one-half. The need for the estimation of intangibles arises from their nature and the accounting principles that govern the recognition of intangibles as balance sheet items. International Financial Reporting Standards (IFRS) define an intangible asset as an "identifiable non-monetary asset without physical substance"[1]. The problem with their recognition lies hence in their nature. Internally generated intangible assets are expensed rather than capitalized since it is often difficult to distinguish between the cost of maintaining or enhancing the firm's operations. The result is an incomplete representation of the value of intangible assets on the balance sheet. Van Criekingen et al. (2022) provide a good summary of the state-of-the-art methods for measuring intangibles. They distinguish between four methods – macroeconomic expenditure approach, survey-based approach, occupation or task-based approach, and firm balance sheet data approach. Only the latter approach is practical for this study due to the requirement of having data available over an extended time frame and on a firm level. The most recent work using the balance sheet approach was conducted by Peters and Taylor (2017). Their work builds among many others on Eisfeldt and Papanikolaou (2013, 2014). However, I am following the latter approach using only accumulated Selling, General & Administrative (SG&A) expenses as a proxy for intangible capital instead of using 30% of (SG&A minus R&D) plus 100% of R&D as proposed by Peters and Taylor (2017). The general viability of using accumulated SG&A expenses stems from research conducted by Lev and Radhakrishnan

[1] https://www.ifrs.org/issued-standards/list-of-standards/ias-38-intangible-assets/#:~:text=The%20cost%20of%20generating%20an,not%20recognised%20as%20intangible%20assets.

(2005), Corrado et al. (2009), and Eisfeldt and Papanikolaou (2013).

3. Data

The accounting data was obtained from Compustat via the Wharton Research Data base (WRDS) on a quarterly basis and the stock return data was obtained from the Center for Research in Security Prices (CRSP) as well as Compustat. Hence, the sample represents the broad U.S. stock market. The sample period for the study is from 2000 until 2020. Fama and French (2016) Factors for their Five-Factor model are obtained from Ken French's[2] website.

4. Method

4.1 Data Curation

Since the Compustat contains duplicates and missing values, some data curation needs to be applied before constructing the signals. Companies that have either more than 10 percent missing values in total assets or SG&A are entirely dropped. This is necessary since a small amount of missing data can be dealt but a higher amount introduces too much noise. With duplicates, I deal in the following way. First, all true duplicates are removed, then duplicates in each company month are addressed. For each company month that exhibits duplicates, the observations are arranged in descending order regarding total assets and SG&A. Then the first observation is kept. This procedure allows me to eliminate the most missing values.

4.2 Asset Growth

I follow the approach developed by Cooper et al. (2008) with the exception that I use quarterly total assets instead of annual total assets. The reasoning behind this is that this allows more frequent portfolio adjustments and should result in a quicker adjustment to

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

changes in total asset growth. Asset growth is hence constructed in the following way, where *it* indicates the asset growth for firm *i* in quarter *t*:

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

4.3 Intangibles Growth

To construct the intangible growth factor, first intangibles need to be estimated by following Eisfeldt et al. (2020) and applying the perpetual inventory method to flows of Selling, General, and Administrative (SG&A) expenses to compute INT_{it}.

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

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:

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

4.4 Intangible-to-Asset Growth

My newly introduced factor Intangible-to-Asset Growth (*IntAssetGrowth*) 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. Hence, the $IntAssetGrowth_{it}$ is constructed in the following way:

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

4.5 Portfolio Construction

In the next step, the data is unsampled from quarterly to monthly observations to fit the return data. 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.

5. Results

5.1 Naïve Performance Analysis

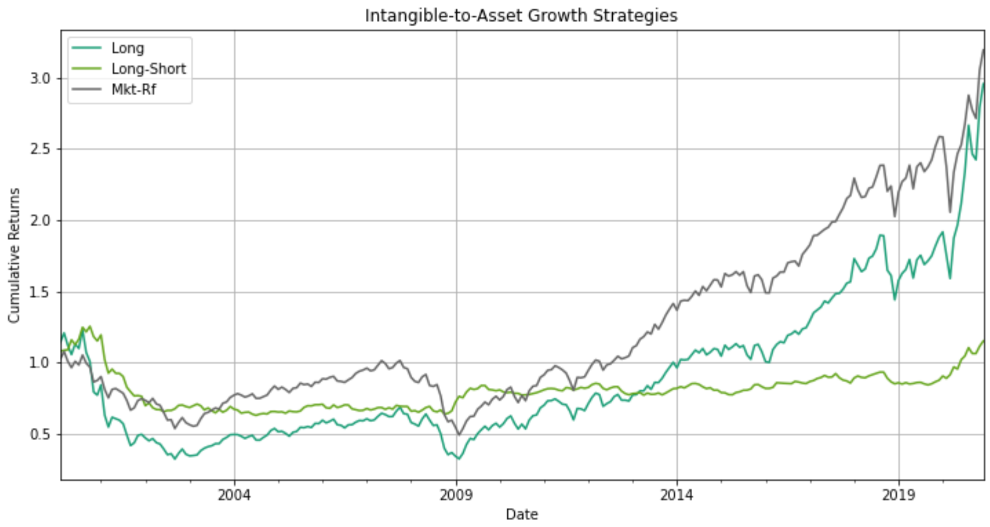

Figure 1: Cumulative Returns of Intangible-to-Asset Growth Strategies

Figure 1 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. It reflects a one-time investment at the beginning of the observation period and monthly rebalancing. Therefore, it serves as a benchmark for the overall market and is hereinafter referred to as the market portfolio. One can see that the long and especially long-short strategies fail to outperform the market portfolio. Over the 20-year timeframe, the long-short strategy in particular barely maintains its initial value. It is noteworthy that the long-short strategy exhibits a gain during the financial crisis of 2008. Table 1 shows the summary statistics for the strategy. Although the arithmetic mean of the long strategy (full sample) is around 0.8 percentage points higher than the arithmetic mean of the market strategy, it falls short regarding its standard deviation and Sharpe-Ratio. The long-short strategy performs disastrously in terms of mean and Sharpe-Ratio. It can only be credited for a rather low standard deviation. Albeit this might be simply caused by the long and short exposure to the market and is not a feature of the Intangible-to-Asset growth strategy.

Table 1: Summary Statistics of Intangible-to-Asset Growth Strategies

	Full Sample (Feb 2000 - Dec 2020)		
	Long	Long-Short	Market
Mean	0.0760	0.0110	0.0683
Standard Deviation	0.2171	0.0921	0.1582
Sharpe-Ratio	0.3500	0.1197	0.4315
	First Half (Feb 2000 - July 2010)		
	Long	Long-Short	Market
Mean	-0.0225	-0.0183	-0.0106
Standard Deviation	0.2458	0.1119	0.1679
Sharpe-Ratio	-0.0916	-0.1631	-0.0631
	Second Half (Aug 2010 - Dec 2020)		
	Long	Long-Short	Market
Mean	0.1753	0.0405	0.1478
Standard Deviation	0.1802	0.0658	0.1449
Sharpe-Ratio	0.9727	0.6160	1.0200

By taking a closer look at the first and second half of the sample period it becomes obvious that the performance is very dependent on the timeframe. While the arithmetic mean of the long strategy is negative for the first decade of the 21st century it surpasses 17.5 percent for the second decade. The performance improvements for the long-short strategy are somewhat smaller but not negligible. However, one should be cautious in attributing this behavior to the strategies themselves, but to the general macroeconomic and market environment. The first decade of the 21st century is characterized by exceptionally low returns in the equity markets and consequently often referred to as a "lost decade" which can be seen by an annualized average loss of about one percent for the market portfolio. In the same way the promising returns of the second half of the sample can be attributed to the overall favorable market environment since the second decade of the 21st century is characterized by high growth rates in the equity markets.

5.2 CAPM Analysis

Table 2 displays the regression analysis for the Capital Asset Pricing Model (CAPM) in addition to the earlier metrics. The CAPM states that there are two types of risk in individual stock investments: systematic risk and unsystematic risk. Unsystematic risk is specific to the business and can be eliminated or decreased by diversification, for example, the risk of new competitors or management problems. Systematic risk is defined as a risk that affects the entire market, including macroeconomic variables like the risk of fluctuating interest rates and inflation.

Table 2: CAPM Regression

	Full Sample		**First Half**		**Second Half**	
	Feb 2000 - Dec 2020		Feb 2000 - July 2010		Aug 2010 - Dec 2020	
	Long	Long-Short	Long	Long-Short	Long	Long-Short
Alpha	-0.0117	-0.0006	-0.0081	-0.0167	0.0007	0.0130
	(-0.694)	(-0.028)	(-0.290)	(-0.493)	(0.040)	(0.669)
Beta	1.2843	0.1695	1.3618	0.1497	1.1811	0.1861
	(41.9762)	(4.8034)	(28.2697)	(2.5674)	(33.6046)	(4.9835)
R2	0.8762	0.0848	0.8657	0.0505	0.9018	0.1680
IR	-0.1532	-0.0063	-0.0898	-0.1528	0.0129	0.2169

The table presents the results of a single-factor CAPM regression. T-statistics are in parentheses.

In the CAPM framework, β_i captures the sensitivity of a security to the market. A beta greater than one indicates that a security is more volatile than the market over time while a beta lower than one indicates less volatility than the market. The CAPM equation takes the following functional form: $E(r_i) = r_f + \beta_i * [E(r_m) - r_f]$. The results of the OLS regressions on the CAPM equation are shown in Table 2. The risk-free return (r_f) is obtained from Ken

French's website and the expected market return ($E(r_m)$) is the return of the market portfolio. The average return of the strategy that the risk factor of the CAPM cannot account for is represented by alpha (regression intercept). Alpha also represents the return from the long and long-short strategies, in comparison to the required rate of return predicted by the CAPM. A positive alpha, therefore, means that the strategy outperformed what was anticipated given the systematic risk of the strategy. We can see that the alphas from both strategies are only slightly positive for the second half of the sample which means that both strategies underperformed the required rate of return suggested by the CAPM during the first half of the sample. The magnitude of positive alphas for the second half is rather small and the values are not statistically different from zero (indicated by the low t-statistics). Hence, an overperformance in terms of the CAPM benchmark cannot be claimed. The betas reveal the high correlation of the long strategy with the market portfolio whereas the performance of the long-short strategy cannot be explained by the exposure to the market. This becomes also evident by looking at the coefficient of determination (R^2). The CAPM model can explain the returns of the long strategy quite well with the exposure to the market but fails to do so with the long-short strategies. The information ratio (IR) measures the returns of the strategies beyond the return of a benchmark, in this case, the market portfolio, compared to the volatility of those returns. A negative IR is not desirable and indicates that there is no benefit in holding such a portfolio. The highest IR exhibits the long-short strategy for the second half of the sample but still cannot reach a competitive level.

5.3 Fama French 3-Factor Analysis

The Fama-French Three Factor Model (FF3) (Fama and French 1992; 1993) extends the CAPM by including two additional factors: "High Minus Low" (HML), which captures the outperformance of a portfolio of stocks with a high book-to-market ratio relative to a portfolio of stocks with a low book-to-market ratio, and "Small Minus Big" (SMB), which captures the outperformance of a portfolio of small-cap stocks relative to a portfolio of large-cap stocks. Table 3 shows the results of the regression on the FF3 model.

Table 3: Fama-French 3 Factor Regression

	Full Sample		**First Half**		**Second Half**	
	Feb 2000 - Dec 2020		Feb 2000 - July 2010		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)
R2	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.

In comparison to the CAPM regression, the alphas change for some subperiods the sign but generally remain close to zero and statistically not different from it. The long-only strategy is well described by the CAPM regression but the FF3 reveals on top of the high exposure to the market risk factor, negative exposure to the HML or value factor. This means that the strategy tends to be exposed to stocks with a low book-to-market ratio. The exposure to the SMB factor is for all subperiods close to zero and not significant. The long-short strategy behaves similarly 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. This means that the long-short strategy tilts towards stocks with higher market capitalizations. Even if exposure to the HML component also has an impact, the slightly increased coefficient of determination (R^2) for the long-only strategy is primarily due to the fact that R^2 improves with more regressors. R^2 for the long-short strategy improves from 0.08 to 0.21 which is substantial and shows that the FF3 model explains the performance of the strategy better than the CAPM. The IRs obtained by the FF3 model show again that the strategies perform poorly.

Due to its low volatility, the long-short strategy has some advantages in terms of risk-reward considerations. It also offers diversification possibilities due to its low exposure to the market factor.

5.4 Strategies as part of a diversified portfolio

Table 4: Strategies as part of a diversified portfolio

	Long			**Long-Short**		
	Long	VTI	BND	Long-Short	VTI	BND
Weight	-1.3%	23.4%	78.0%	3.4%	20.6%	76.0%

To assess the usefulness of a strategy it is important to analyze how what role it can play in a well-diversified portfolio. For that reason, I construct mean-variance efficient portfolios for each strategy, Vanguard Total Stock Market ETF (VTI), and the Vanguard Total Bond Market ETF (BND). Those ETFs are chosen because they are easily investible and broadly cover the stock and bond market, respectively. Table 4 shows the weights of the portfolios and reveals what I have discussed in previous sections – the long and long-short strategies build based on the Intangible-to-Asset growth factor do not improve a well-diversified portfolio and there seems to be little reason to invest according to it.

5.5 Drawdown

To assess the downside risk, a look at the drawdown of the strategies is helpful which is the peak-to-trough decline of the strategies (Figure 2). The drawdown plot reassures what previous analyses have found – the Intangible-to-Asset growth strategy is not compatible. The long-short portfolio does not recover to a peak for almost 20 years and the long-only strategy exhibits a maximum drawdown of over 70 percent. This shows that the long and long-short strategies expose an investor to substantial downside risk and offer limited upwards potential.

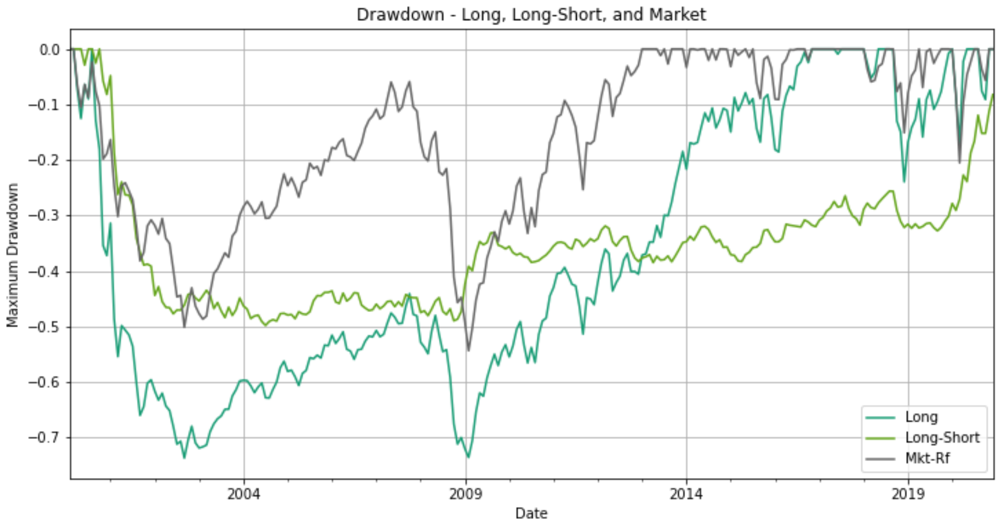

Figure 2: Drawdown of Intangible-to-Asset Growth Strategies

5.6 Improving the strategy

To find improvements and reasons for the underperformance of the Intangible-to-Asset growth strategy, I dissect the strategy into its components: asset growth and intangible growth. Additionally, I use annual instead of quarterly Compustat data to build the signals.

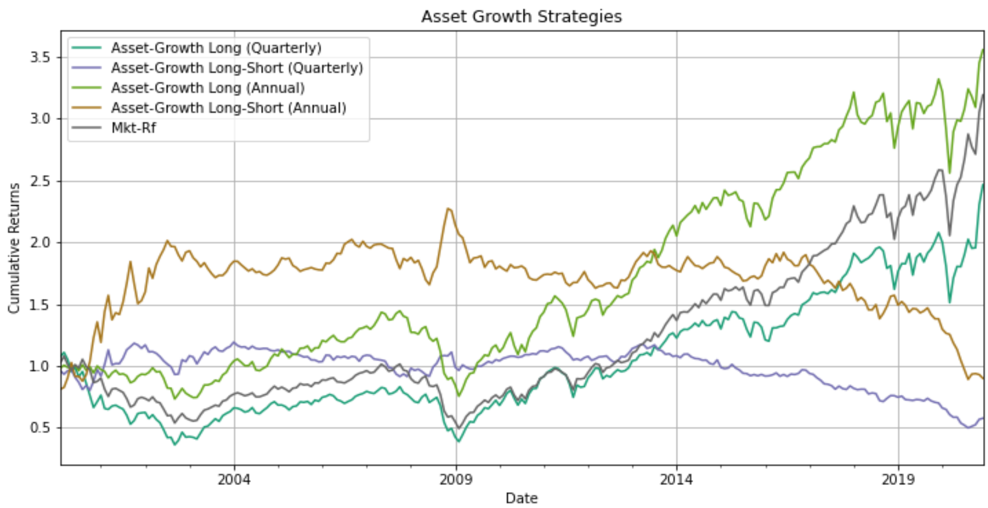

Figure 3: Cumulative Returns of Asset Growth Strategies

Figure 2 shows the cumulative returns of various Asset Growth strategies. It is evident that the long and long-short strategies formed by using annual fundamentals perform better than their quarterly counterparts which hint towards the first problem of the Intangible-to-Asset growth strategy. Furthermore, it is noteworthy that the asset growth effect (Cooper, Gulen, and Schill 2008) cannot be replicated at all with quarterly data. Regarding annual data, a strong asset growth effect is only observable until 2009. During the second decade of the 21st century, the long-short portfolio performed so poorly that the cumulative return at the end of the sample is negative. Explanations for this can be, in my opinion, twofold. Either something changed in the market environment so that the asset growth effect vanished, or the returns were simply so high in the years following the financial crisis that any portfolio with substantial short exposure to equities would suffer losses.

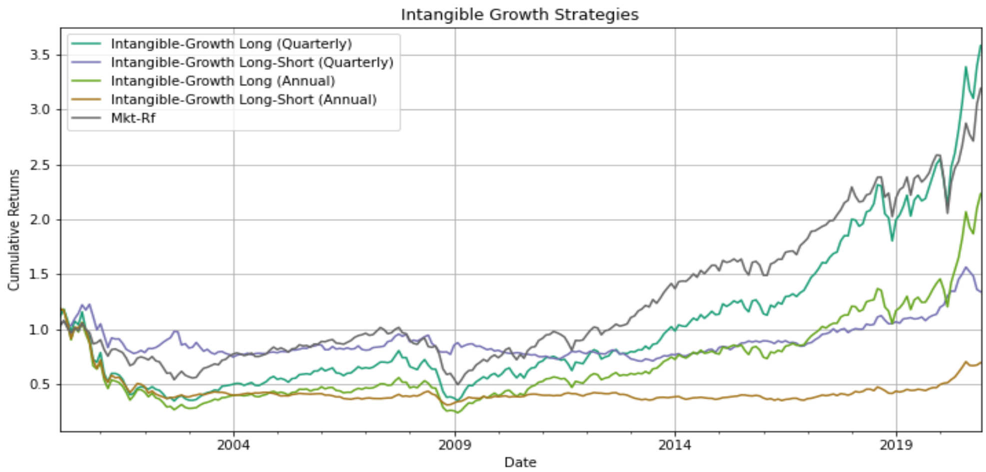

Figure 4: Cumulative Returns of Intangible Growth Strategies

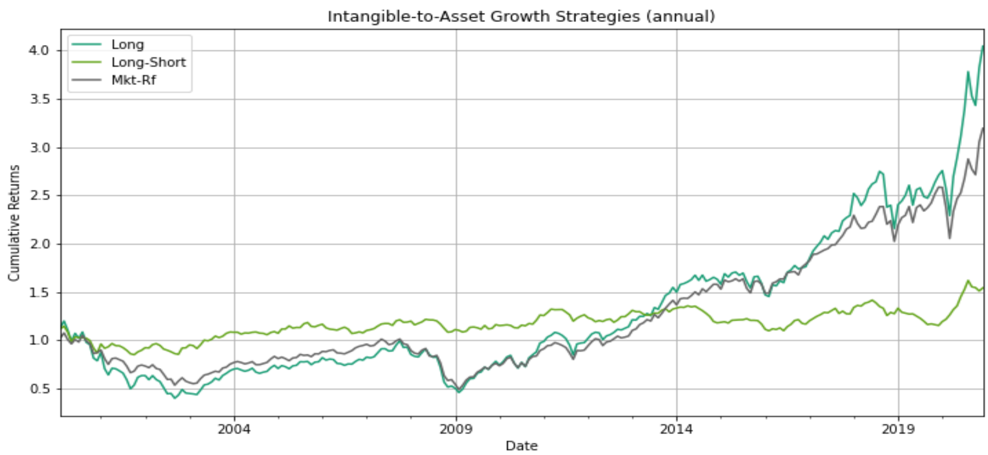

Figure 5: Cumulative Returns of Intangible-to-Asset Growth Strategies (annual)

Figure 4 shows the cumulative returns of various intangible growth strategies that reveal another reason for the poor performance of the Intangible-to-Asset growth strategy. Intangible growth cannot predict future stock returns very well. Only the Intangible-Growth strategy built with quarterly data has higher cumulative returns than the market portfolio. Hence, the asset growth part of the strategy is likely suffering from noise in the estimation of the growth factor and intangible growth could not prove that it can predict future stock returns. Figure 5 shows the cumulative returns of an Intangible-to-Asset Growth strategy relying on annual fundamental data. It shows that the benefits of quicker portfolio readjustments due to more frequent data are outweighed due to the added noise.

6. Conclusion

I find that the Intangible-to-Asset Growth strategies fail to provide abnormal risk-adjusted returns over time. The long and long-short strategies exhibit substantial downside risk with limited upward potential. Only the long-short strategy provides potential diversification benefits for a broad portfolio due to its low volatility. However, the process of building the strategy is complicated and requires investments in various equities that possibly incur high transaction costs. Reasons for the underperformance of the strategy can be found in its parts. The asset growth effect cannot be replicated with quarterly total asset data and even for annual total asset data, it seems to vanish during the second decade of the 21st century. The difference in performance is most likely the result of noise that gets added to the growth estimation when using quarterly data. Also, intangible growth does not have predictable power on its own. The reasons for that are manifold. It can be due to a low correlation between intangible growth and stock returns or due to a suboptimal approach to estimating the value of intangible assets.

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