Picking Outperformers in the Technology Sector

Using financial statement analysis and analyst recommendations
- Evidence from U.S. listed technology stocks.

Master thesis

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Abstract

This study examines whether a multi-signal-based stock-picking approach, on financial statement analysis and analyst recommendations, can select outperformers among U.S. Listed technology companies. The so-called "GASCORE", created in this research, is tested against 1504 U.S. listed technology companies over a twenty-year time period starting from 1998. Thereby, enhancing the understanding on whether accounting-based fundamentals are properly incorporated in the stock price. Statistical tests show that the GASCORE can pick outperformers among the sample of technology companies, even after controlling for the Fama and French 3 and 5-factor models. Indicating that a simple fundamental analysis strategy can shift the distribution of returns. Moreover, this research concluded that the GASCORE can separate winners from losers. Implying that a long-short portfolio based on this approach is feasible, even though the practicality of implementing this strategy may be difficult.

Table of Contents

1. Introduction

Performing a fundamental analysis based on financial statements is difficult and time-consuming. Moreover, with the large scope of public traded companies, it is impossible to properly go through all of them separately. To know whether a company is worthwhile analyzing, there should be certain criteria in place for initial selection. Otherwise, investors will make decisions that are the most satisfactory but not the most efficient due to their bounded rationality (Magni, 2009). Because of these time limitations, investors will only consider companies that come to their attention through news, colleagues, or websites. Consequently, how does one objectively pick the best stocks without being subjected to arbitrary surroundings and biases? To address these issues, this paper will build upon previous literature that generated a multiple-signal-based score to separate winners from losers (Piotroski, 2000; Mohanram, 2005). The approach in the paper of Mohanram (2005) will be followed as the technology sector, analyzed in this research, is closely related to the sample of low book-to-market stocks. As the score is based on fundamental analysis, growth companies are expected to be valued differently from value stocks due to their financial statement characteristics (Damodaran, 2009). The so-called "GASCORE" created in this research, is a more specific multiple-signal-based approach to match the characteristics of the technology sector. The goal of this paper is to determine whether *the GASCORE can pick outperformers among U.S. Listed technology companies*.

The valuation method that is currently still preferred to determine the value of a company is the Discounted Cash Flow ("DCF") model (Reinert, 2019). Within the DCF model, the future earnings are estimated and afterwards discounted to put a price on a company. This model is especially useful for companies with predictive earnings and revenue growth rates (Damodaran, 2001). For companies with less predictive earnings, assumptions on growth rates are harder to make, thereby, making valuations more difficult. Moreover, when the industry growth rates are relatively uncertain, it makes valuations even harder as assumptions are built upon assumptions. The technology sector has the highest P/E ratio of the five biggest sectors in the U.S., inferring the high expected growth rate of this industry (Yan et al., 2020). Technology stocks with high expected growth rates are associated with higher volatility due to higher uncertainty and speculation, making these investments riskier (Imbs, 2007). Given the scale of the technology sector, it is important to understand the characteristics of these companies, to help investors avoid large losses. This paper will analyse what financial statement characteristics are vital for outperformers in the technology sector. Thereby, giving investors an indication of what items are important to consider in the decision process of picking technology stocks.

This research will contribute to the academic literature by adding understanding on the efficiency of the stock market. If markets are fully efficient, financial statement analysis should not be able to pick outperformers as the information is available to all market participants (Malkiel, 1989). Nonetheless, the outcomes in this paper indicate that fundamental analysis is still a useful tool in picking outperformers. The importance of determining this is linked to retail investors. Retail investors are more prone to sentiment-based investing compared to professionals, and consequently, missing out on valuable returns (Kumar & Lee, 2006). Moreover, to decide whether as an investor the opinion of experts is important to improve returns, the analyst consensus is added as an investment signal. This will enhance the understanding of the value of fundamental analysis in determining investment opportunities in growth companies. Moreover, the GASCORE is compared to a previous score on a broader sample. Thereby, increasing the understanding of whether value drivers differ across industries, and whether it is translated into higher returns. This can be useful for managers of technology firms, to understand the financial statement characteristics that are important to focus on to create value. Furthermore, it can be a useful guideline for investors to determine the financial statement items that need more attention. At last, the multiple-signal-based approach will provide more understanding on the value of combining signals to base investment decisions on. Investment signals or indicators can have little predictive power on returns used separately. Nonetheless, by combining they can be valuable.

Within the academic literature, several papers have been published to pick outperformers. For instance, investing in companies where the founder is still CEO is associated with an excess return (Fahlenbrach, 2012). Moreover, companies that did perform well in the last 3-12 months tend to have an abnormal return compared to the rest of the market (Blitz et al., 2020). Furthermore, the most established anomalies within the literature were published in the paper of Fama and French (1992). In this paper, the value premium and size premium were added to the market risk premium in the capital asset pricing model ("CAPM"). While these factors tend to outperform, they are associated with additional risk. Small companies tend to have higher volatility and value stocks have a bigger chance of financial distress. These investment strategies on factors investing were based on single indicators. To take this one step further, additional literature analyzed whether a combination of financial statements items can separate winners from losers. The first one to implement this was Piotoski (2000), in which the "FSCORE" was created. This score is grounded on a simple accounting-based fundamental analysis strategy with multiple binary signals. He showed that for a large sample of high book-to-market firms it increased the annual return by 7.5%. Subsequently, Mohanram (2005) contributed to the literature by creating a multiple-signal-based approach for low book-to-market firms. Low book-to-market companies are valued differently from high-book-to-market stocks as they have different financial statement characteristics (Damodaran, 2009). Therefore, the score based on fundamental analysis differs for the two samples. The multiple-signal-based approach (called the GSCORE) from Mohanram (2005), showed to earn an excess return for a long-short strategy.

This paper will elaborate on the sole financial statement analysis by adding analyst recommendations. As the literature is not clear about the predictive power of analyst recommendations, the signal will first be analyzed separately. It is interesting to determine whether professional analysts can separate winners from losers, within the uncertain environment of high speculative growth stocks. The research is performed by taking a sample of 1504 U.S. listed technology stocks from 1998-2018. The GASCORE is derived from the GSCORE (Mohanram, 2005) with some adaptations that will be discussed in the research design. The multiple-signal-based approach will have eight binary signals for each company year. The correct binary score for the individual signals is determined by cross-sectional yearly data, for the whole 20 years in the sample. For every signal that meets the criteria, a binary score of 1 is generated. For yearly company values that do not meet the criteria a binary score of 0 is created. The binary scores of 1 are expected to be indications of proper investment opportunities.

The first three signals measure the degree of revenue, earnings, and cash flow profitability. While the first signal in the GSCORE is based on earnings, the first signal in this research is based on sales growth. This deviation is made since growth stocks, and especially for young growth stocks, the earnings are uncertain. Therefore, analysts tend to look at revenue growth to give them guidance

(Bartov et al., 2002; Zhao, 2018). The next signal is based on cash flow profitability. For companies with high growth, earnings are not present, especially in the early stage. This is due to large investments in tangible and intangible assets (Ittner, 2008). For example, in order to build a strong brand, initial investments are needed. These investments will not immediately be translated into additional earnings, as it takes time to exploit it (Schiuma et al., 2008). The two most commonly used indicators for performance evaluation are net income and cash flow from operations ("CFO"), respectively (Nwaeze et al., 2006; Perry & Zenner, 2001). The amount of money a company brings in with its regular business activated is measured by the CFO. Managers are incentivized to manage earnings by making use of the flexibility of accounting principles. One example of this is channel stuffing. Channel stuffing is a business practice used to inflate revenue and net income by sending more products along the distribution channel than the customer will buy or use (Lai et al., 2011). This goes against the principles of accounting standards that financial statements should reflect a company's performance objectively and accurately (Tung et al., 2008). Therefore, to measure the degree to which these fraudulent accounting practices happen, the next signal measures the difference between the net income and the cash flow from operations.

Furthermore, to determine the degree of naive extrapolation, the following two signals are based on revenue and earnings stability. Naive extrapolation is the prolongation of market trends in the market predictions by not taking variability into account (Tsuji, 2006). Thereby, making irrational decisions. Companies with lower variance in their sales and earnings are not only more persistent, but they also have a lower probability of underperformance (Levis & Liodakis, 2001). To measure this degree of persistence, the fourth and fifth signals consist of companies with the lowest variance in earnings and revenue.

At last, the subsequent three signals are based on the growth opportunities of the company. For technology stocks, growth is strongly linked to the exploitation of innovative products and investing in R&D is therefore crucial (Lantz, 2005). Moreover, companies that invest excessively in R&D expenses are associated with being more long-term oriented (Cescon, 2002). Therefore, the sixth signal is based on the research and development expenses of the company. The seventh and eighth signals are again deviations from the GSCORE in which the signals are based on accounting conservatism. Nevertheless, to measure the growth opportunities the seventh signal is based on analyst recommendations. Earlier research found that purchasing stocks with the highest consensus estimates, yields an abnormal return (Barber et al., 2001). In addition, following analyst recommendations for asset allocation in international markets produces excess returns (Berkman & Yang, 2016). Thereby, implying the predictive power of these analysts' recommendations which is expected to enforce the signaling power of the score. This goes against the efficient market hypothesis that states that share prices fully reflect all available information (Malkiel, 1989). This paper will evaluate the predictive power of analyst recommendations by looking at the consensus of multiple analysts. The last signal is based on the return on invested capital ("ROIC"). ROIC is used as a fundamental method of determining a company's financial performance. In the valuation book of McKinsey, it is broadly explained and said to be the best indicator to determine whether a company is creating value with the capital that is being re-invested (Koller et al., 2010). Companies that have a strong competitive advantage can express this in high returns and long-run outperformance, which is measured as the ROIC. Companies that have a ROIC below their weighted average cost of capital will destroy value over time and can better distribute dividends instead of re-investing (Demodaran, 2007). Therefore, companies with a higher ROIC than the sample median will be seen as proper investment targets.

In the subsequent chapter, the theoretical background of the relevant academic literature will be discussed in the literature review. Successively, in chapter 3 the research design will be explained. Thereby, explaining the signals used in the creation of the GASCORE, which is afterwards followed by the methodology. Successively, the data will be analyzed and discussed in chapter 4. This is done to get a proper understanding of the data this research is working with. Moreover, the results will be discussed in chapter 5. After that, conclusions will be drawn based on the findings of this research in chapter 6. In addition, the limitations of the research and the future research recommendations will be discussed followed by the references and the appendix.

2. Literature review

The following section will describe the theoretical background of the relevant academic literature. This is necessary to get a good understanding of the relevance of signals that are used within this research. Initially, the importance of top-line growth versus bottom-line growth will be discussed in section 2.1. Furthermore, the significance of cash flow from operations will be addressed, and thereby also the link with net income in chapter 2.2. Moreover, in section 2.3 the academic research on earnings and revenue stability will be discussed and the relationship with technology stocks. Additionally, the signals for growth opportunities will be reviewed. Which are the research and development expenses (2.4), the analyst recommendations (2.5), and the return on invested capital (2.6). At last, the Fama and French 3 and 5-factors will be discussed in section 2.7.

2.1. Top-line growth

Traditional valuation methods like the Discounted Cash Flow Model rely on future earnings to put a price target on companies (Damodaran, 2001). Unfortunately, for growth stocks and especially young growth stocks, these are uncertain. Moreover, it is hard to put a growth rate on negative earnings (Damodaran, 1999). Therefore, analysts tend to look at revenue growth to give them guidance. For technology stocks, which are characterized as high-growth stocks especially in the early lifecycle, several pieces of literature have indeed confirmed this. In the paper of Bartov et al. (2002) on the valuation of internet stocks, sales and sales growth were already seen as a better value determinant than earnings. Furthermore, high-growth companies are often associated with negative earnings due to the exploitation of future options (Zhao, 2018). Therefore, an increase in net loss year over year could be associated with a large number of investment options which is a positive signal. In the absence of earnings, revenue is seen as the lifeblood of these companies to determine the amount of growth, as the expectation is that profits will follow at a later stage (Bartov et al., 2002). This underlying assumption is debated within academic research as these deficits are hard to turn around. For hyper-growth companies, which are companies with growth rates of more than 500% over five years, no link was found between profitability and extreme growth (Markman & Gartner, 2002). Implying that the high-level reliance on revenue may be outstretched.

2.2. Cash flow from operations versus net income

The two most used indicators for performance evaluation are net income and cash flow from operations ("CFO"), respectively (Nwaeze et al., 2006). Earnings are seen as the go-to performance measure, but CFO tends to be increasingly important. In a survey of 200 companies from the S&P 500 and Midcap 400, literature found that 15 percent of these firms use CFO as a performance measure (Perry & Zenner, 2001). Thereby, showcasing the rise towards CFO as a valuable performance measure. The incentive to manage earnings by managers by making use of the flexibility of the generally accepted accounting principles ("GAAP"), explains this shift.

One example of earnings management is channel stuffing. Channel stuffing is a business practice used to inflate revenue and net income by sending more products along the distribution channel than the customer will buy or use (Lai et al., 2011). This typically occurs just before year-end or quarter-end to meet performance targets (Das et al, 2011). Managers should be focused on long-term targets and inflating earnings is seen as improper behaviour. Moreover, this goes against the principles of accounting standards that financial statements should reflect a company's performance objectively and accurately (Tung et al., 2008). Therefore, it is more appropriate to rely on CFO as a performance indicator as it is less subjective and harder to inflate. It is more difficult to inflate as the CFO considers the cash a company is bringing in from its regular business practices. In the example of channel stuffing, customers are often given extended payment dates which boost short-term earnings but decrease these earnings in the long run. As CFO looks at the cash that is coming in, accounts receivables are not considered (Lai et al., 2010). Furthermore, earnings tend to be depressed in the early stage of companies, due to the investments in fixed assets and intangible assets (Piotroski, 2000). Therefore, the difference between the two performance measures gives a good indication of the amount of accounting conservatism. To estimate accounting conservatism in this paper the difference between CFO and net income is taken as a proxy. Especially, as earlier research found that relying on the exceedance of CFO to net income is not a useful signal (Mohanram, 2005).

2.3 Earnings and revenue stability

The subsequent signals, based on earnings and revenue stability, will estimate the amount of naive extrapolation. Naive extrapolation is the irrational prolongment of market trends in market predictions by investors (Tsuji, 2006). Thereby, not considering the volatility of the earnings and revenue. When two companies have the same amount of sales and earnings, and all the other factors are ceteris paribus, their valuations should be the same. Now consider company X and company Y, where company X has more stable earnings. The chance that the strong performance in a certain year is due to luck, is bigger for company Y. The probability of underperformance in the following year is therefore higher for company Y. Companies with lower variance in their revenue and net income are not solely more persistent, but they also have a lower probability of underperformance (Levis & Liodakis, 2001).

Adding these signals to the GASCORE should improve the model as earnings persistence is rewarded by investors (Dechow et al., 2010). Whether these indeed predict outperformance for technology stocks is still ambiguous as there is little literature on this. Technology stocks are associated with explosive growth, which may be more important for investors than stable growth, especially in the early stage (Damodaran, 1999). Moreover, for the valuation of companies, stable earnings are more convenient as they are easier to predict and thereby leading to lower stock price volatility (Dichev and Tang, 2009). Companies with low volatility are associated with higher returns compared to high-volatility stocks. This anomaly is known in the literature as the low-risk effect (Baltussen et al., 2020). Besides, companies with stable sales tend to have more positive returns and a lower skewness than companies with unstable revenues (Lamp, 2015). Thereby, not only increasing performance in absolute terms but even more on a risk-adjusted basis.

2.4 Research and development

The first indication that is used to signal a company's growth opportunities is the amount of research and development ("R&D") expenses. For technology companies, growth is strongly linked to the exploitation of innovative products. Investing in R&D is therefore crucial (Lantz, 2005). R&D expenses also decrease the short-term financial results of companies, as they are long-term investments with high uncertainty. Implying that, companies that have relatively high R&D expenses are more long-term orientated. This is beneficial for company performance, as long-term-orientated companies tend to outperform companies that are more short-term focused (Flammer & Bansal, 2017). These R&D expenses depress current earnings in the short term but are linked to an increase in future growth opportunities.

Investing in R&D also leads to the creation of intangible assets. The option value gained from this research cannot be converted into hard assets immediately. Moreover, putting too little importance on intangibles leads to underperformance in the long term (Ittner, 2008). For example, investing in innovation leads to customer satisfaction and increased product quality, which eventually leads to better competitive advantage and market share (Corona, 2009). By underinvesting in these items, the long-term performance of companies is severely impacted. Furthermore, research found that there is no outperformance of companies having R&D expenses compared to firms without any R&D expenses (Lantz, 2005). Nevertheless, stocks with high R&D equity to market value, earn excess returns as investors are too pessimistic about the beaten-down earnings of these companies (Chan et al., 2001). On the other hand, companies with high R&D expenses are associated with higher price volatility. Suggesting that there is more information asymmetry between investors and R&D-intensive firms (Gharbi, 2014).

2.5 Analyst recommendations

Analysts provide in-depth market research for their clients to base investment decisions on. These reports indicate whether stocks are undervalued or overvalued which is translated into buying or shorting opportunities. Stock prices move significantly if analysts revise their recommendations implying their importance for a company's valuations (Jegadeesh & Kim, 2006). Especially in the short-run (2-day returns), there is an excess return by rapidly investing after upgrades due to the increased attention for these revised stocks (Green, 2006). Moreover, portfolios consisting of the highest analyst recommendations outperformed the market from 1986 to 1996 even after less frequent rebalancing (Barber et al., 2001). Thereby, adding to the evidence of the ability of analysts to pick winners in the stock market. Nonetheless, there is also contradicting evidence on the predictability power of these reports. In the research of Baker and Dumont (2014), they found that stocks that were included in the "buy" recommendations of analysts underperformed "hold" ratings.

Furthermore, additional research found that even tough equity analysts were able to distinguish outperformance on a relative basis. They were less informative on the absolute target prices (Da & Schaumburg, 2011). This is not surprising, as equity analysts are focused on a few stocks within a sector. Therefore, they are more capable to rank companies than predicting macro-economic factors which are necessary to predict price targets. Besides, analysts from sell-side firms typically recommend "glamour" stocks. Which are companies with strong momentum, high volume and that are relatively expensive (Jegadeesh et al., 2004). These companies tend to have higher valuation multiples, more positive accounting accruals and higher capital expenditures. All in all, the literature is mixed on the forecasting power of analysts. Moreover, there is little research on the predictive power of these analysts within the technology sector, this paper will elaborate on this issue.

2.6 Return on invested capital

The last signal is based on the return on invested capital ("ROIC"). ROIC is a fundamental method of determining a company's financial performance. In the equation below, the formula is displayed to get a good understanding of this performance indicator.

$$Return\ on\ Capital\ (ROIC) = \frac{Operating\ Income_t\ (\ 1\ -\ Tax\ Rate)}{Book\ Value\ of\ Invested\ Capital_{t-1}} \tag{1}$$

The motive to take operating income into account as a performance measure is to consider the return generated on the whole capital invested. If net income would have been used, the earnings to lenders would have been ignored. Furthermore, the book value of invested capital is used instead of market value because the market value includes the expected value of growth assets. In our sample, Microsoft had a tax-adjusted operating income of 8.25 billion in 2007 and a market capitalization of 300 billion. By taking the market capitalization into account in determining the ROIC, the return on invested capital would be less than 3%. While taking the book value of 31 billion a more reasonable return on capital of around 26.5% is found (Demodaran, 2007). Thus, especially for companies with high expected growth like the technology sector taking the book value is important. At last, there is a lag in the book value of invested capital. This is used to determine the return over a one-year period.

In the valuation book of McKinsey, ROIC is broadly explained and said to be the best indicator to determine whether a company is creating value with the capital that is being re-invested (Koller et al., 2010). Companies that have a strong competitive advantage can express this in high returns and long-run outperformance which is measured as the ROIC. Companies that have a ROIC below their weighted average cost of capital will destroy value over time and can better distribute dividends instead of re-investing (Demodaran, 2007). In a fast-paced environment like the technology sector, it is important to repeatedly find new investment opportunities in order not to lose the competitive advantage. In a report by Mckinsey (2007) on growth versus ROIC, they found that the emphasis of fast-growing companies is on growth even if it decreases the return. Eventually, when the industry matures and there is less room for growth, companies should return capital to shareholders in the form of buybacks. In this paper, ROIC will be used as an indication of whether a company can find profitable investment opportunities. This is crucial to gain insight into whether a company can gain market share in the long term.

2.7 Fama and French 3 and 5-factor models

To evaluate the returns of the different GASCORES, the returns must be adjusted for factors that tend to outperform. Otherwise, this multiple-signal-based approach could just separate companies that tend to outperform based on their characteristics, instead of finding pure outperformers. The signal based on analyst consensus is already subject to analysts recommending "glamour" companies instead of undervalued companies (Jegadeesh et al., 2004). To adjust for these factors that did historically outperform, the returns are adjusted based on the three-factor asset-pricing model shown in the equation below (Fama & French, 1992).

$$r = r_f + \beta_1(r_M - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon_i \tag{2}$$

The expected rate of return is independent of the risk-free rate, which is an approximation for the time value of money (Thomsett, 2018). By subtracting the risk-free rate from the expected return, the excess return is obtained. To explain this excess return, Fama and French added 3 factors: The market risk premium, the size premium, and the value premium. The market premium explains the difference in return between treasury bonds and the equity market. The beta of the market risk premium is determined by comparing the volatility of a single stock against the overall market (Sharpe, 1964). Volatility is associated with risk, and therefore the return should be higher for more volatile companies. Especially for our sample, this beta is higher than the overall market as technology stocks are associated with higher volatility (Schwert, 2002). Moreover, the size premium (SMB) is a tendency of companies with smaller market capitalizations to outperform firms with larger market capitalizations (Fama & French, 1992). The rationale behind this is that small stocks are riskier and therefore investors should be compensated for the additional risk. Therefore, it is important to adjust the returns by these factors to evaluate the outperformance of investment strategies. At last, the value premium expressed in the high minus low variable (HML), represents the spread in returns between the value stocks against the growth stocks. Companies with high book-to-market values tend to outperform low book-to-market companies (Fama & French, 1995). Stocks with high book-to-market values have a higher chance to be in financial distress and these are firms that are less favoured by investors. To compensate for this additional risk, part of the excess return is explained by this variable.

In 2015, Fama and French came up with even more explanatory variables to describe the return on assets (Fama & French, 2015). They added the profitability and investment factor to the value and size premium. This was a surprise for many academics as the momentum factor was not added to the regression. Despite, it being widely accepted within the academic literature (Cooper et al., 2004).

$$r = r_f + \beta_1(r_M - r_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(RMW) + \beta_5(CMA) + \varepsilon_i \tag{3}$$

In the equation above, the Fama-French 5-factor model is presented. The first explanatory variable that is added to the 3-factor model is RMW. This is the return difference between stocks of robust profitability and weak profitability (Fama & French, 2015). Implying that companies with higher profitability are associated with an increase in the expected return. In addition, the CMA factor is included to explain expected returns. Companies that invest conservatively have higher expected returns than firms that invest aggressively. All the variables together explain between 71% and 94%

of the cross-sectional variance of the expected returns. There is one side note of adding these factors to the 3-factor model, the value factor appears to be redundant in describing returns after adding the RMW and CMA variables (Fama & French, 2015). Notwithstanding, the 5-factor model has higher explanatory power and is, therefore, more suitable to adjust the returns of portfolios with. Moreover, the signals used in the GASCORE may have some overlap with the 5-factor model. For instance, the RMW factor which is based on profitability is probably correlated with the signals GA3 and GA4 which both consider earnings. Both the 5-factor model and the GASCORE are linked with finding companies that outperform. The main difference is that for the Fama and French factors the anomalies are linked to higher risk and therefore investors should be compensated for it (e.g. value premium and higher risk of distress). However, for the GASCORE, this is not necessarily the case (e.g. higher ROIC is not associated with higher risk).

This paper will create an adjusted GASCORE (GASCORE*) based on the Fama and French three-factor model. This is done to determine whether there is an ability to pick outperformers in the technology sector after correcting for these anomalies. Furthermore, a GASCORE** is created. This is the GASCORE adjusted for the Fama and French 5-factor model. Thereby, adding to the Fama and French 3-factor model by also controlling for the profitability and investing anomalies. The yearly returns of the different portfolios are adjusted for both the 3-factor model and the 5-factor model. This is done by regressing the individual factors from the Fama & French website, against the yearly return of the portfolio (French, 2021). Thereby, determining the betas. Afterwards, the betas are multiplied by the average of the yearly Fama & French factors of the sample period. By adding up the different factors the cost of equity is determined. The cost of equity is subtracted from the average portfolio return minus the risk-free rate. Resulting in the adjusted return.

3. Research design

The subsequent section will explain the research design of this paper. This is essential to understand how the individual signals for the GASCORE are formed. First, an overview of the previous multiple-signal-based scores performed in the literature is given in chapter 3.1. Secondly, the signals based on revenue, earnings and cash flow profitability are discussed in section 3.2. Moreover, naive extrapolation will be discussed in chapter 3.3. Thereby, explaining how these indicators will empower the research. Furthermore, in section 3.4 the formation of the signals based on growth opportunities will be explained. At last, the hypotheses will be formulated in chapter 3.5.

3.1 Overview of previous scores

Investors in the stock market are looking for an excess return by applying fundamental and technical analysis. Thereby, trying to outperform passive investing into an index fund. For technical analysis, there are several studies suggesting that there is an alpha by investing based on technical indicators (Gerritsen, 2016). Unfortunately, there is market friction in the form of transaction costs and shorting restrictions, which makes most of these strategies not feasible for practical implementation (Nazário et al., 2017). The critics of fundamental analysis state that markets are efficient and all available information is translated into the stock price (Malkiel, 1989). This view is frequently rejected within the literature as the stock market does not seem to be fully efficient. Earlier examples on the outperformance of analysts invigorate this view (Barber et al., 2001; Green, 2006). Moreover, the strict definition of the efficient market hypothesis ("EHM") of being fully rational is almost certainly false, leaving room for financial statement analysis (Sewell, 2011).

Within this research, the market inefficiently will be analyzed by following a signal-based approach on the U.S. listed technology stocks. There has been prior research performed on this topic. Piotroski (2000) found that a multiple-signal-based approach on fundamental analysis can favourably shift the distribution of the portfolio of investors. The "FSCORE" created in this research was derived from earlier research in which only one indicator was used based on the ROE (Penman, 1991). Piotroski (2000) elaborated on this topic, by adding multiple signals that empowered each other, thereby trying to find outperformers within a portfolio of high book-to-market companies.

Subsequently, Mohanram (2005) followed a similar approach of investing based on a score formed out of multiple signals. Thereby, mainly focussing on low book-to-market stocks. In this research, the approach of Mohanram (2005) will be followed as the "GSCORE" is more similar to the technology stocks used in this sample. The companies used in the sample, have relatively low book values compared to their market value due to their growth opportunities. The median is taken to determine whether companies are proper buying opportunities. This way of measurement is used to give equal weight to the individual signals. For scores that would have been rated from 1-4 based on quartiles, a score of four would have been equal to four signals with a score of 1, which is arbitrary. Therefore, a simple way of measurement is used in which the sample is split into two categories; 1 for a buying opportunity and 0 if not.

The literature will be followed by constructing a "GASCORE", for which historical financial statements are used. Moreover, to determine the value of the analyst recommendations, the overall consensus is used as an estimation. In the following section, the different signals will be explained. First, signals for earnings and cash flow profitability will be discussed. Followed by, signals for naive extrapolation that are used to estimate the quality of the earnings and the revenue. At last, the signals to indicate growth opportunities will be reviewed.

3.2 Signals based on revenue, earnings and cash flow profitability

The initial signals are used to estimated revenue and cash flow profitability. Companies that are currently growing and have a high asset turnover, tend to be valued higher by investors (Purnamasari, 2015). This is especially true in growing industries. Firms that have relatively high asset turnover compared to other companies within the industry, tend to sustain this over time (Sunjoko et al., 2016). This is translated into more robust performance compared to their peers with low asset turnover. The technology sector is still a growing industry, and since this paper aims to filter out the fundamentally strong companies, the first signal is based on asset turnover. *GA1 is equal to 1, if the asset turnover is greater than the cross-sectional median asset turnover in the sample, and 0 otherwise.*

The next signal is based on cash flow profitability. For companies with high growth, earnings are not present, especially in the early stage. This is due to large investments in tangible and intangible assets. For example, in order to build a strong brand, initial investments are needed that will not lead immediately to additional earnings (Schiuma et al., 2008). By determining the return on assets ("ROA") with the operating cash flow, these expenses are not considered. The CFO indicates the amount of cash that is coming in by the regular business activity. By dividing the CFO by the average assets, it gives a good estimation of the relative amount of cash the company is generating. The average assets are calculated by taking the assets in the year of the ROA calculation and adding up the assets of the previous year and dividing them by two (Lai et al., 2010). This leads to the following signal. *GA2 is equal to 1, if the cash flow from operations ROA is greater than the cross-sectional median in the sample, and 0 otherwise.*

The last indication estimates the soundness of the earnings. To estimate this, earlier research compared the earning to the CFO (Mohanram, 2005). For low book-to-market companies, this signal showed to be insignificant. In order to add a signal that is more relevant the difference between the CFO and net income is taken. It is not only an approximation for the soundness of the net income, but it also adds to the conservatism of the accountants. Companies that are more conservative are more eager to invest in intangible assets and therefore build a more sustainable company in the long term (Orhangazi, 2019). The signal will be based again on the cross-sectional median. The cross-sectional median is the median for a certain year within our sample. This is used in order to split the companies into two groups, which will be determined based on the following signal. *GA3 equals 1 when the cash flow from operations minus the net income is greater than the cross-sectional median within the sample, and 0 when the difference is smaller than the median.*

The different signals are used to exploit the company characteristics that are overlooked by investors. The effectiveness of these signals is ambiguous even though it is substantiated by literature. Earlier research took larger sample groups that were less specific (Piotroski, 2000; Mohanram, 2005). The sample used in this paper is more specific since it is completely focused on technology stocks. To get a better impression of the effectiveness of our signals, they will be analyzed separately in the results.

3.3 Signals based on naive extrapolation

The following two signals are based on naive extrapolation. Investors tend to be too focused on specific seemingly attractive investment options. A well-known cognitive bias is narrow framing. In the context of narrow framing, investors are overlooking the bigger picture of all the investment possibilities (Jain et al., 2015). Thereby, leading to sub-optimal investment decisions based on irrationality. As discussed in the literature review (2.3 Earnings and revenue stability), two companies with the same earnings and sales can have different probabilities of outperformance or underperformance in the preceding year. In order to separate the companies with lower earnings variance from the firms with higher variability, the fourth signal will be used. The variability of the earnings will be determined by using quarterly data over four years. Contrary to the other signals, this binary score will be equal to one if the variance is smaller than the median. *GA4 is defined to be equal to 1 when the earnings variability is smaller than the cross-sectional median within the sample, and 0 otherwise.*

The second indicator for naive extrapolation will be based on the consistency of the sales growth. Companies with consistent revenue growth are likely to continue this pattern. As investors focus to extensively on the current growth rate, they don't consider enough the past growth rates (Piotroski, 2000). Therefore, companies with higher fluctuation in their growth rates are expected to underperform. Moreover, literature documented that there is a presence of representativeness bias in the interpretation of consistent sales growth (Ahmed & Safdar, 2017). Companies that have historically low variance in their earnings and revenue have a higher probability of being mispriced as investors do not sufficiently price this valuable company characteristic. Therefore, with the next signal, this research distinguishes between companies with more consistency in their revenue growth. Which is based again on quarterly data. *GA5 is defined to be equal to 1 when the revenue growth variability is smaller than the cross-sectional median within the sample, and 0 otherwise.*

The signals for naive extrapolation are found in earlier research to great extent (Ahmed & Safdar, 2017) (Piotroski, 2000; Mohanram, 2005). In our sample, which consists of technology companies for a time horizon of 20 years the effectiveness of these signals is unclear. The preference for consistent earnings and revenue growth may be less present in a booming industry. Moreover, the preference for stable earnings and revenue growth could also shift over time. For example, investors value these characteristics more for companies in a later maturity stage compared to the start of the dot-com bubble. Therefore, the explosive growth of the internet and the companies that came together with it, may have shifted the preference of investors (Loomis & Taylor, 2012). By looking at the individual signals this paper will indicate investor's preference within a fast-growing industry.

3.4 Signals based growth opportunities

The last three signals are used to give an indication of the growth opportunities. R&D expenses indicate the amount of cash that a firm spends to have future growth opportunities. In addition, analyst recommendations are used as a proxy for a perceived growth opportunity and option value compared to the current stock price. The analyst consensus presents the opinion of experts compared to the overall market. At last, the ROIC is a check for the current returns a company gets over the re-invested capital that is not returned to shareholders. For the technology stocks in this paper, the investments in research to come up with new products and services are crucial for the sustainability of the competitive advantage and market share (Lantz, 2005). By weighting the R&D expenses with the total revenue, the amount spent on future growth opportunities can be compared. This indicates how long-term-oriented finance managers within the company are. When managers are only focused on short-term profitability to meet the target, it will hurt the company in the long run. Especially with higher-pressured firms, which are companies where finance managers perceive relatively high short-term pressure, managers are focused more on cost reduction than investing in innovation (Cescon, 2002). Therefore, the following signal is a measure for future growth opportunities but also the long-term orientation of companies. *GA6 equals 1 when the R&D expenses are larger than the cross-sectional median within the sample, and 0 when the difference is smaller than the median.*

The following signal is based on the analyst recommendations. This gives a proper estimation of the overall consensus within the market given the current stock price. Professional stock analysts give a recommendation whether to buy, hold or sell a stock based on a score from one to five. A score of one is equivalent to a strong sell, two equals a sell, and three indicates that investors or clients should not sell or buy at the current price. Analysts that display a score of four suggest that the company is currently undervalued and that there is a buying opportunity, while five is the highest score and equal to a strong buy opportunity. By looking at companies that have a higher buy rating than the cross-sectional median in our sample, it indicates which companies analysts prefer given the price. This paper is using the median instead of every value above 3 (which are all buy ratings) since analysts are also subject to certain biases which overestimate their stock-picking capabilities (Hong & Kacperczyk, 2010). Therefore, they tend to overvalue the companies within their scope, as analysts generally get a specific industry they analyse. The capabilities of analysts seem to be more pronounced in their ability to pick relatively overvalued or undervalued companies instead of the capability to determine absolute valuations (Da & Schaumburg, 2011). The seventh signal is prepared through the following criteria. *GA7 is equal to 1 if the analyst consensus is larger than the cross-sectional median analyst consensus within the sample, and 0 otherwise.*

The last signal is based on the return on invested capital. Which approximates the company's capability to find profitable investment opportunities within their business area. Firms that have a ROIC that is lower than their weighted average cost of capital, destroy value and can better return money to shareholders in the form of share repurchases or dividends (Demodaran, 2007). Therefore, companies that have high ROIC can find profitable investment opportunities. In addition, these companies tend to be able to sustain these returns. Implying that these companies are robust and fundamentally strong (Heegaard, 2013). The ROIC is created by taking the operating income, subtracting the tax rate, and dividing this value by the book value of invested capital in the previous year (see chapter 2.6 for a more detailed explanation). This value provides an easy-to-understand percentage value that demonstrates how the company is performing with the reinvested capital. *GA8 is defined to be equal to 1 when the ROIC is bigger than the cross-sectional median within the sample, and 0 otherwise.*

The last two signals based on growth opportunities are not previously used within the literature for the creation of a score based on fundamentals. For the technology stocks, the growth opportunities are crucial for the survival of these companies, as they rely on innovative products. Within the results, the separate signals will be analyzed to give a handhold on the usefulness of the signals. In figure 1 the signals are summarized that together translate into the GASCORE.

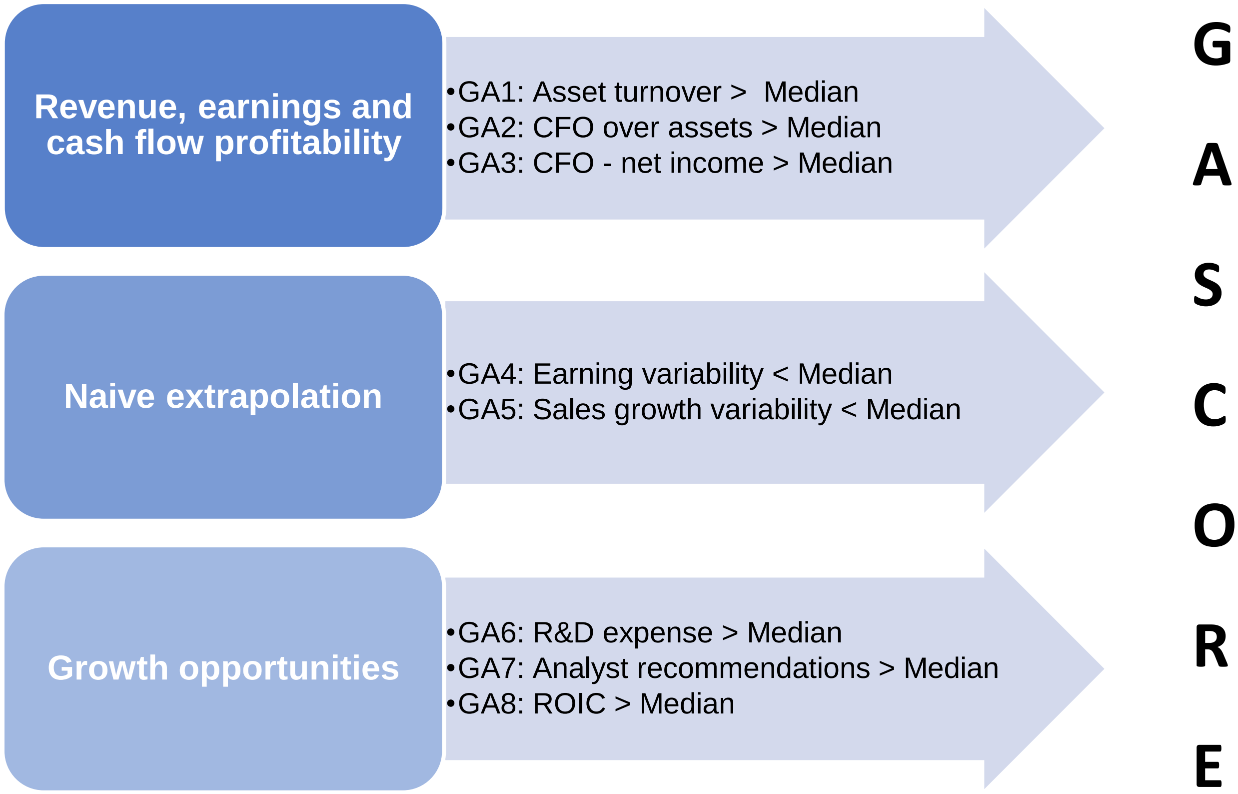

Figure 1: **Overview of the signals resulting in the GASCORE**

Note. The GASCORE is formed by the sum of all the individual signals. The signals return a binary score of 1 or 0. Therefore, the highest GASCORE a company can get in a certain year is 8.

3.5 hypotheses formulation

In the following section, the hypotheses are discussed. These are used to determine the effectiveness of the GASCORE. In the literature review and the research design, the signals are empirically substantiated separately. Nonetheless, this combination of the signals is not previously performed in the academic literature, and therefore the hypotheses will be used to determine the validity of the model.

Previous literature already demonstrated that there is an excess return by investing in companies with high scores based on multiple financial statement signals (Piotroski, 2000; Mohanram, 2005). The signals for the GASCORE are more specific for the technology sector and to measure the consensus of the different companies the analyst recommendations are added. This paper expects that based on the GASCORE better-performing companies can be separated from firms with lower returns.

Hypothesis 1a: The GASCORE can pick outperformers among U.S. Listed technology companies.

Hypothesis 1b: The GASCORE can distinguish between winners and losers among U.S. Listed technology companies.

The first hypothesis is verified by comparing the results of the highest GASCORE to the overall sample. A one-sample t-test is performed to determine whether there is a significant difference between the mean returns. The second hypothesis is tested by performing a two-sample t-test on the returns of the different GASCORES. Thereby, determining whether the GASCORES of 7-8 minus 0-1 is statistically different from zero. Furthermore, the returns of the scores of 2 & 6 and 3 & 5 are matched together to see whether the difference is equal to zero. The middle score of 4 is not used to test the hypothesis as it is ambiguous whether it should be positive or negative.

In the research design, this paper substantiated the decisions to deviate from the GSCORE. This is done to have a score that is more suitable to the sample of technology stocks used in this paper. Therefore, the GASCORE is expected to be better at picking outperformers than the GSCORE for the sample of technology stocks.

Hypothesis 2: The GASCORE is more capable of identifying outperformers among U.S. Listed technology companies than the GSCORE.

The GASCORE deviated in four ways from the GSCORE. First, instead of having a signal based on the return on invested assets the asset turnover is used. Top-line growth is more important for fast-growing technology companies than bottom-line growth (Purnamasari, 2015) (Sunjoko et al., 2016). Secondly, a signal based on CFO minus net income is used instead of CFO which is bigger than the net income. In the paper of Mohanram (2005), this signal was not positive and significant but even negative and significant. Implying that it had a negative effect on the capability of splitting winners and losers. Therefore, to create a useful signal the CFO minus net income is taken to give an approximation for the soundness of the net income (Orhangazi, 2019). At last, the advertisement and capital expenditures are replaced by the analyst consensus and ROIC. This is done to construct a bucket of signals that contribute to the growth opportunities of technology firms instead of accounting conservatism, which is more important for the technology companies (Lantz, 2005) (Cescon, 2002). The effectiveness of the GASCORE compared to the GSCORE is measured by performing a one-sided two-sample t-test. The scores of 7-8 of the GASCORE are subtracted from the GSCORE to determine whether the difference is negative. If the difference is indeed significantly higher than zero, the GASCORE is better at picking outperformers among technology stocks.

As discussed in the literature review (2.7 Fama and French 3 and 5-factor models) it is important to determine the outperformance of the scores after correcting for the market risk premium, small stock premium and the value premium. By not taking the market risk premium into account, the signal can be separating companies solely based on their market beta. Thereby, not correcting for the higher risk of more volatile companies. Consequently, not picking outperforming companies on a risk-adjusted basis. Moreover, the GASCORE could be separating value and small stocks which are getting a higher return because they are riskier. Furthermore, to determine the ability of outperformance after correcting for the operating profitability and investment style of the companies, the returns are adjusted for the Fama and French 5-factor model. To determine whether the GASCORE can pick outperformers after correcting for these factors, the following hypotheses are stated.

Hypothesis 3a: The GASCORE can pick outperformers among U.S. Listed technology companies after correcting for Fama and French 3-factor model.

Hypothesis 3b: The GASCORE can pick outperformers among U.S. Listed technology companies after correcting for Fama and French 5-factor model.

To measure the outperformance after correcting for the Fama and French 3-factor model, the GASCORE* is created. This is done by subtracting the cost of equity from the excess return (as discussed in 2.7 Fama and French 3 and 5-factor models). For the Fama and French 5-factor model, the GASCORE** is created using the same method. The different scores are tested against the whole sample by performing a one-sided t-test.

4. Data

The following section will describe the data used in this paper. This is important to get a proper understanding of the validity of the conclusions. Initially, in section 4.1 the descriptive statistics are given. Moreover, the method in which the data is gathered is described and explained. Furthermore, the revenue (4.2), net income (4.3), return (4.4) and analyst recommendations (4.5) are laid out to get a better understanding of the distribution of these variables. At last, the correlation of the variables will be analyzed in section 4.6.

4.1 Descriptive statistics

All the data in this research is gathered through Bloomberg. To check the gathered data, Capital IQ is used. Capital IQ is a market intelligence platform that is used by finance professionals to collect financial data for public and private companies. In order to collect the U.S. listed technology companies, the equity screening (EQS) function from Bloomberg is used. For the years from 1998 until 2018, all the companies classified under U.S. listed technology companies, according to Bloomberg, are collected. To have unbiased data, all the companies for the specific years are added together. Subsequently, all the duplicates are deleted from this group. The U.S. listed technology companies that remain are after this procedure are 1504 in total. For the signals which eventually lead to the GASCORE, yearly and quarterly data is used. To give an overview of the difference in count per year, chart 1 (In the appendix) is shown. The companies classified under technology stocks have been declining since 2005. This is a primary indication that the technology sector has been consolidating leading to fewer and bigger companies.

Quarterly data is used to calculate the binary values for the naive extrapolation. Multiple data points are needed to get a good estimation of the historical variance. Thereby, calculating the variance of the earnings and the revenues, based on the previous four years. This is done in the same manner as earlier research suggested (Piotroski, 2000; Mohanram, 2005). This also explains the chosen time horizon in this paper, since the data was available from 1994. Since there are four years of available data needed to get a good approximation of the earnings and revenue variance, the first scores are created in 1998. To estimate the performance of the scores, returns after one year are analyzed. In order to exclude the companies without enough observation, firms with less than 12 quarterly data points are excluded and classified as not available. In Table 1, the descriptive statistics of the quarterly data are shown.

Table 1. Descriptive statistics of quarterly data.

Variables	Count	Mean	Median	Standard deviation	Min	Max
Net Income ($ mln)	68984	44.86	0.98	524.32	-41848	28755
Revenue ($ mln)	68193	488.01	51.28	2386.74	-2	111439

The financial information used is based on quarterly data from financial statements for 1504 companies. The time period used is from 6/30/1994 until 12/31/2018. The companies are selected through Bloomberg by including all U.S. technology stocks with a market capitalization above 100 mln $.

For the other signals, yearly data is used. There are three reasons for the use of yearly data. First, the portfolio rebalancing will be done every twelve months as quarterly rebalancing is not practical. The filling date of companies is several weeks to months after the fiscal date. As the stocks have different fiscal dates quarterly data would lead to data that is hard to compare. Therefore, taking the data from the annual report is more practical. Moreover, yearly rebalancing also lowers the transaction costs compared to quarterly rebalancing. By using the reported date, the investment decision would have been based on data that is not available yet. Therefore, to not have hindsight, the portfolio returns of the filling date are used instead of the reported date. Second, the quarterly data from Bloomberg compared to Capital IQ is more subjected to error. In the data check between the two databases, the quarterly data appeared to be less accurate. The variance is explained by the different dates for the filling date which leads to a comparison of two different fiscal quarters. At last, this paper follows previous literature which also chooses to take yearly data as a research method (except from the earnings and revenue variance) (Piotroski, 2000; Mohanram, 2005).

In the Table below the descriptive statistics of the variables used for the different signals are shown. The count is the number of company years for which the data is available. For instance, Juniper Networks, a company that went public in 1999 and still exists today, will only have 19 data points instead of 20. Since the first year of data is missing. The count is lower than if all the companies were available for the whole sample period, as many “promising” companies classified under technology stocks went bankrupt or got acquired. The high standard deviation (compared to the mean) is due to the distribution spread of the sample. For example, the revenue of the technology stocks prior to the dot-com bubble was close to zero, while the revenue of apple in 2018 was over 250 billion dollars (referring to the max revenue in Table 2). This is a large deviation from the sample mean.

Table 2. Descriptive statistics of yearly data

Variables	Count	Mean	Median	Standard deviation	Min	Max
Revenue ($, mln)	15877	1728.59	184.63	8404.94	0	265595
Cash Flow From Operations ($, mln)	15897	301.69	12.51	2203.07	-4640	81266
Net income ($, mln)	16038	139.14	1.46	1583.89	-56122	59531
Assets ($, mln)	15789	2344.10	232.06	12157.79	0	375319
Analyst recommendations (1-5)	17025	3.77	3.83	0.96	1	5
Research and Development ($, mln)	13009	164.79	21.75	771.55	0	14726
Return on Invested Capital (%)	13101	-18.09	7.28	1587.60	-174109	12218
Market Capitalization ($, mln)	12888	5450.94	476.65	31976.48	0	1073306
Total Shareholder Return (%)	12101	21.64	2.53	112.38	-1	25

The financial information used is based on yearly data from financial statements for 1504 companies. The time period used is from 1998 until 2018. The companies are selected through Bloomberg by including all U.S. technology stocks with a market capitalization above 100 mln $ (for at least 1 period). Analyst recommendations are based on a average score from 1 to 5. The score 5 indicates a strong buy and a score of 1 is equal to a strong sell.

4.2 Revenue

To understand the distribution of revenues in the technology sector, chart 2 gives an overview of the year over year (“YoY”) growth and the yearly average revenue in the sample. The average revenue growth is around 8%, with large negative deviations from the mean after the burst of the dot-com bubble (-2% and -9%) and after the financial crisis (-6%). Noteworthy is also that in 2000 the crisis was characterised by high revenue growth (18%). While in the financial crisis the highest growth rates were seen after the economic collapse (17% and 17% in 2010 and 2011). In these 20 years, the revenue grew by more than 350%. As this is partly explained by the increase of the technology market, the sector also consolidated. In 1998 there were 933 companies (with available revenue data) classified as U.S. listed technology companies, while in 2018 there were only 536. Indicating that there are fewer bigger companies in a larger market.

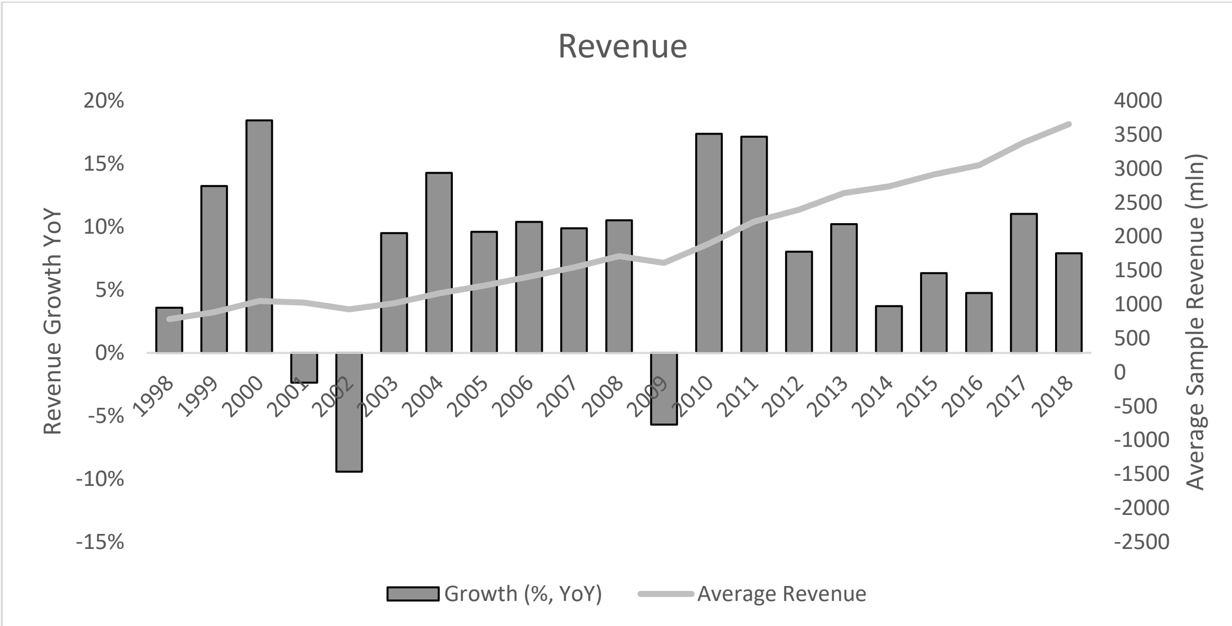

Chart 2: **Overview of the revenue growth and the yearly average revenue in the sample**

Note. The left y-axis is linked to the bar chart of the revenue growth year over year. For the 21 years used within this sample, there were only 3 years of negative revenue growth. On the right y-axis, the average revenue in the sample is matched to the line diagram.

4.3 Net income

Furthermore, To gain better insights into the profitability of the technology market, chart 3 is displayed. The growth of sales is not enough to understand the value creation within the sector, as the industry can be growing and still destroy value. The cross-sectional standard deviation is added to understand the effect of crises on the variability of earnings. As shown, the crash after the dot-com bubble, had a severe impact on the net income variance within the sample. In appendix figure 2, the income statement of JDS Uniphase is shown from the annual report in 2001. This is the highest yearly loss within the sample. In the case of Uniphase, the company had to write off more than 50 billion dollars in goodwill. The goodwill impairments are a recurring reason for large earning losses. Especially for technology companies, acquisition prices are much higher than the value of the net assets due to the growth potentials. In the dot-com bubble, the growth expectations were surpassing rationality (Meltzer, 2003). Therefore, acquisitions that were overpaid, had to re-evaluate the goodwill which led to huge losses in the aftermath. This even resulted in negative average earnings for the sample. Moreover, the financial crisis in 2008 also caused a decrease in net income, but on the contrary, the earnings variability did decrease instead of increase across time. All in all, the technology sector has established itself as a profitable industry with more than 200 million dollars of average profits in the last 9 years.

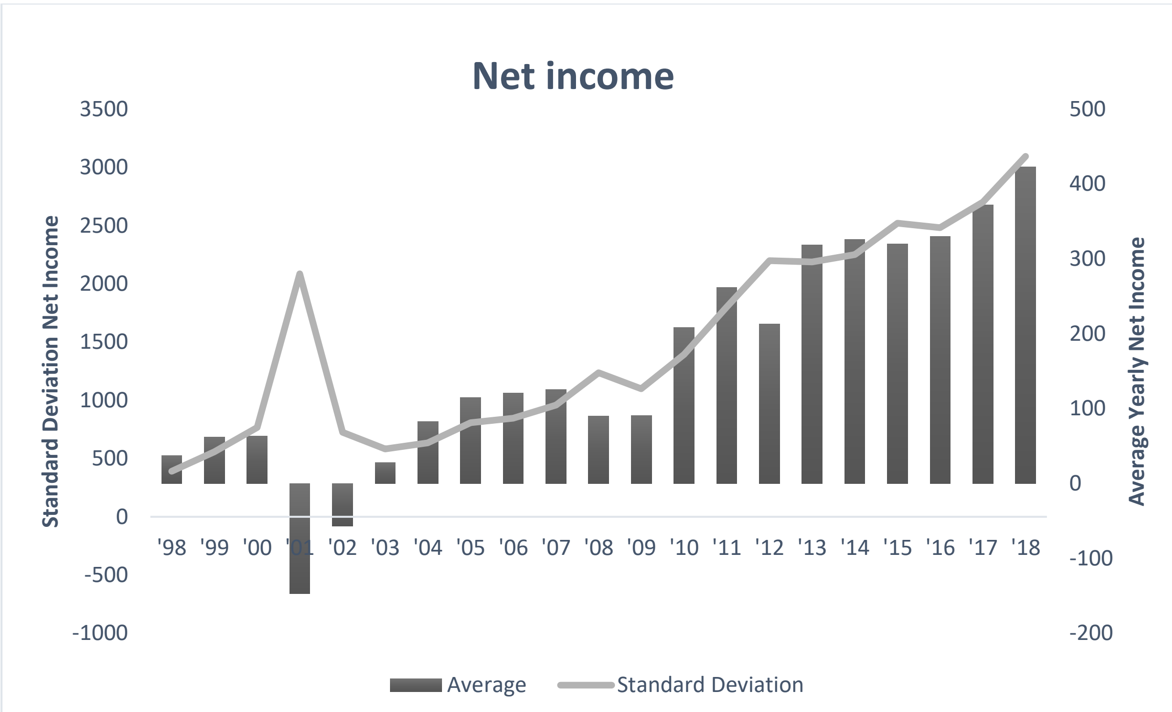

***Chart 3:* Overview of the average net income and the standard deviation of the net income in the sample of technology stocks**

4.4 Return

After having looked at the top-line and bottom-line growth within the technology sector, it is also important to understand the stock returns within the industry. The returns for the determination of the GASCORE are based on yearly returns given portfolio rebalancing. Therefore, high fluctuation in stock prices can positively skew the distribution. When a company goes bankrupt the maximum loss is 100%, while theoretically, the upside of a company is unlimited. This is indeed what Chart 4 illustrates. The data has a skewness value of 6.55 indicating that the tales of the distribution are longer or fatter on the right side. In this sample due to the asymmetry of the returns, the tales are longer on the right side than on the left side of the distribution. The positive skewness in combination with yearly portfolio rebalancing (without considering transaction costs and price spreads) can lead to higher average returns than the benchmark. This paper will go more in-depth on this issue within the result section. In chart 5, within the appendix, the returns above 200% are displayed. More than three-quarters of the returns are between 250% and 500% and most of these returns are originated in the years 1999 and 2000. Again, enforcing the irrational stock mania that happened around that time. For instance, LightPath Technologies, Inc. (LPTH) went from a stock price of 33$ in October 1999 to 376$ in a time span of only 3 months (appendix chart 6). Three years later, the stock tumbled to a low of 1.27$. This is one of the examples of stocks with particularly high yearly returns. It also indicates the risks involved (especially in the early stage) with investing in technology companies. As mentioned in the literature review (2.1 Top-line growth), the stock prices are highly dependent on the sentiment of investors since revenues and earnings are uncertain.

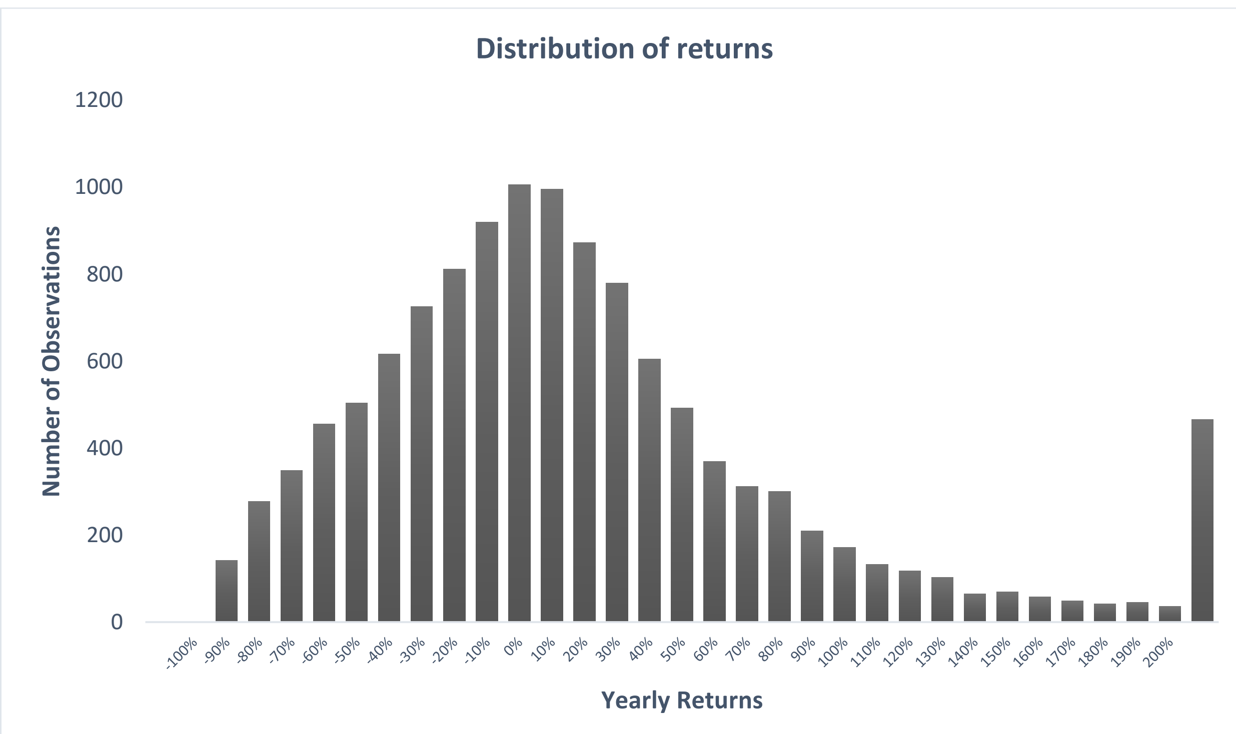

Chart 4: **Overview of the distribution of total shareholder return**

4.5 Analyst recommendations

The analyst recommendations represent the average consensus for a specific stock for a given year. The score ranges from one to five. For which one equals a strong sell, two a sell, three a hold and four and five a buy and strong buy, respectively. In an efficient market, the average analyst consensus should be equal to three as the price should reflect all the available information about stocks (Malkiel, 2003). Nonetheless, that is not what is found in our sample as the median is 3.77. Especially with the introduction of the Regulation Fair Disclosure, in which public companies are prevented from selective disclosure of information to professionals, analysts are not expected to have superior data compared to other market participants (Securities and Exchange Commission, 2000). In the results (section 6.1), this paper will research whether analysts are indeed able to pick better-performing stocks on a relative basis. Since analysts get a set of companies within the same sector to determine the value of these companies. Analyzing the technology sector, should give an appropriate indication of whether they can pick outperformers.

4.5 Correlation

In Table 3 the correlation between the eight signals is displayed. The correlation is measured by first calculating the appropriate signals and afterwards determining the correlation between the binary scores. The highest correlation is between GA2 (cash flow from operations over assets) and GA8 (the return on invested capital). This is understandable as the CFO indicates the amount of cash a company earns with its ongoing business and the ROIC is the return a company generates with the earnings that are re-invested. Furthermore, the ROIC has the operating income in the numerator and therefore there should be a strong link between these variables. The highest negative correlation is between GA2 and GA3, which again are signals that are both based on the CFO. The low correlation between the signals already gives an indication of the distribution of the GASCORES. When correlations are low the chances of companies having GASCORES of eight in which all the signals are equal to one are nihil. Moreover, the chance that companies with eight signals returning zero are also nihil. Therefore, the expectation is that the extreme scores (both low and high) have small counts.

Table 3. Correlation between the individual signals in the GASCORE

Variables	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8
GA 1: Asset turnover > Median	1,000	0,101	0,138	-0,012	0,040	-0,270	0,016	0,093
GA 2: CFROA > Median	0,101	1,000	-0,302	0,164	0,255	-0,216	0,041	0,312
GA 3: CFO - NI > MEDIAN	0,138	-0,302	1,000	-0,051	-0,200	0,044	0,138	-0,099
GA 4: Earnings variability < Median	-0,012	0,164	-0,051	1,000	0,186	-0,060	0,011	0,231
GA 5: Revenue growth variability < Medi	0,040	0,255	-0,200	0,186	1,000	-0,100	-0,034	0,124
GA 6: R&D expenses > median	-0,270	-0,216	0,044	-0,060	-0,100	1,000	-0,033	-0,151
GA 7: Analyst recommendations	0,016	0,041	0,138	0,011	-0,034	-0,033	1,000	0,006
GA 8: ROIC > Median	0,093	0,312	-0,099	0,231	0,124	-0,151	0,006	1,000

The table above represents the correlation for the different signals in the GASCORE. The signal represent a binary score of 0 or 1 for 1504 U.S. listed technology companies from 1998 until 2018. The correlation between the individual binary signals are measured across time.

5. Methodology

In section 5.1 the formation of the GASCORES is introduced. Moreover, the statistical tests that have been used to determine the validity of the results are explained. In addition, the reasoning behind the formation of the GSCORE is examined in section 5.2. Furthermore, the GASCORE* and GASCORE** will be discussed in section 5.3. Thereby explaining, in which way these additional scores empower the findings of this paper.

5.1 GASCORE

The goal of this paper is to determine whether the GASCORE can identify outperformers among U.S. Listed technology companies. In the research design, the reasoning behind the chosen signals is broadly explained. In figure 3, an example of the individual signal (GA1) contributing to the overall GASCORE is shown. For signal one, the different asset turnovers are compared against a cross-sectional median of the sample. Companies with a yearly asset turnover that is higher than the median are given a score of one and zero vice versa. The eight signals are summed together and translated into one score. Companies without available information are given a "not available" ("n.a."), which is translated into a score of zero. When all the scores are equal to n.a., or the total shareholder return is not available, the scores are not taken into account. It is possible that a company has a score of eight in $Year_t$, while having a score of zero in $Year_{t-1}$. Each year the returns of the companies for a certain score are summed up and afterward the averages are taken to measure the return. In this way, the portfolios based on the GASCORE are equally weighted with yearly rebalancing. The disadvantage of this method is that the exposure of smaller companies is higher than by taking the weighted average. As stocks with smaller market capitalizations are riskier, this can influence the required return of the portfolio (Fama & French, 1992). Indexes as the S&P 500 weigh their exposure to the market capitalization of the companies in the portfolio. Thereby, having more fluctuation in the portfolio return for larger companies compared to smaller firms. Furthermore, this method does not consider transaction costs and bid-ask spreads that would normally affects the returns of investors in practice.

Asset turover (%)

	Company X	Company Y	Company Z	…..	Median
Dec/04	0.5	0.2	n.a.		0.35
Dec/05	0.7	0.4	n.a.		0.30
Dec/06	0.2	0.2	n.a.		0.40

	Company X	Company Y	Company Z	…..
Dec/04	1	0	n.a.	
Dec/05	1	1	n.a.	
Dec/06	0	0	n.a.	

GA1

	Company X	Company Y	Company Z	…..
Dec/04	5	4	n.a.	
Dec/05	4	3	n.a.	
Dec/06	2	6	n.a.	

Figure 3: **Example of the contribution of GA1 to the formation of the GASCORE**

After having formed the GASCORES, the averages are taken over the yearly returns to determine the overall return. These returns are compared to the mean returns of the whole sample to decide whether they underperform or outperform. In the formula below, the calculation of the return of the GASCORE of zero (for a certain year) is shown as an example. First, the proper GASCORE for all the companies is determined. Thereafter, the returns of the appropriate scores are summed up. Afterwards, to obtain the return of the portfolio the total return is divided by the number of scores in a certain year. With this method, yearly rebalancing is taking into account since every year a new portfolio of companies is formed. The mean return of the whole portfolio is calculated by taking the average of all the returns from 1998 until 2018.

$$Return_{GASCORE_{0_t}}\left(Company_{a_t} \ldots Company_{x_t}\right) = \frac{IF\ Company_{a_t}(GASCORE = 0\ \mathrm{I}\ Return_{t+1}) \ldots + IF\ Company_{x_t}(GASCORE = 0\ \mathrm{I}\ Return_{t+1})}{N_{GASCORE=0_t}} \quad (4)$$

To determine the volatility of the portfolio the standard deviation of the yearly returns is measured. Subsequently, to measure the statistical significance of the differences between the whole sample and the individual scores, a one-sample t-test is used. To determine whether the GASCORE can pick outperformers among the sample the following null hypothesis is formulated;

H_0: $The\ return\ difference\ between\ the\ whole\ sample\ and\ the\ highest\ GASCORE\ is\ equal\ or\ smaller\ than\ zero$

To decide whether the null hypothesis can be rejected the mean return of the whole sample is subtracted from the mean return of the GASCORE of 7-8. The expectation thereby is that based on the multiple-signal-based approach, the GASCORE can identify the companies that outperform the overall industry. Therefore, the mean return for the highest GASCORE should be higher than the whole sample. The null hypothesis will be rejected when the difference between the two portfolios is significantly higher than zero for a 5%-significance level. The one-sample t-test used to determine the significance level is shown in formula 5.

$$t = \frac{x - \mu}{s \,/\, \sqrt{n}} \tag{5}$$

Where, x is the return of the GASCORE, μ is the return of the whole sample, s is the standard deviation of the GASCORE, and n is the number of available returns for a given GASCORE. Furthermore, to determine the return adjusted for volatility the Sharpe ratio is calculated. The Sharpe ratio was developed by Sharpe (1964) to understand the relationship between return and risk. In the sample of technology firms, the risk-free rate which is taken from the Fama and French website (2021), is subtracted from the return on the GASCORE. Afterward, it is divided by the standard deviation of the portfolio (see formula below).

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

To get a proper understanding of the risk-return relationship for the different scores and the whole sample, the Sharpe ratios are compared against Three benchmarks. The first benchmark is the S&P 500, which is a proxy for the wide U.S. stock market. Even though, it is a broad index market, is increasingly dominated by technology companies that account for a large percentage of the total market capitalization (Lin & Chang, 2015). Especially, as all the companies are in some way dependent on technology the distinguishment is becoming harder to make. Secondly, the NYSE Archa Tech 100 index is the more specific benchmark of the technology stocks that are listed on the New York Stock Exchange. It is one of the oldest indexes that track the technology sector of U.S. listed companies and it is therefore comparable to the sample used in this paper. At last, the average of the whole sample is used to determine the outperformance of the portfolio. As the NYSE Archa Tech index applies certain criteria for companies that are added to the index, it does not give a proper understanding of the overall market of U.S. listed technology stocks. The sample used in this research is expected to be a more relevant performance evaluator for the different GASCORES.

Furthermore, to identify whether the GASCORE is able to separate winners from losers. The returns between the different portfolios of scores are compared. The mean return of the GASCORE of 0-1 is subtracted from the GASCORE of 7-8. This difference is expected to be the highest between the portfolios of GASCORES, since they are separated with the most binary points. Given that only the difference is positive and significant for this score, then the ability to separate winners from losers is low. Moreover, the GASCORE of 2 and 6 are compared. Assumed that the different is also positive and significant, the GASCORE's ability to separate winners from losers is moderate. At last to determine whether the GASCORE has a high ability to separate winners from losers, the score of 3 and 5 are compared. To test whether the differences are significant, the following hypothesis is used.

$$H_0\text{: } The\ return\ difference\ between\ the\ two\ GASCORES\ is\ equal\ or\ smaller\ than\ zero$$

The null hypothesis will be rejected with a significance level of 5%. To test this a one-sided two-sample t-test is performed. This is done to test the mean return differences between the two samples of portfolios. To two-sample t-test is shown in formula 7 (Cressie, 1986).

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s^2(\frac{1}{n_1} + \frac{1}{n_2})}} \tag{7}$$

Where, $\bar{X}_1$ is the return on the highest GASCORE and $\bar{X}_2$ the return is on the lower GASCORE. The s^2 is the pooled sample variance, which is multiplied by the sample sizes (n_1, n_2), which are divided by one and added up. By dividing the numerator by the square root of the denominator the t-value is obtained. The ability to separate winners from losers is tested to determine whether a long-short portfolio can be created with the GASCORE. A long-short portfolio does buy companies that are expected to rise in value and sell stocks that are expected to decline (or rise less) in value (Jacobs, 1999). This strategy is interesting as a long-short portfolio is expected to be balanced (risk-neutral) and thereby the alpha can be exploited with leverage. The practicality of the long-short portfolio will not be researched due to the time limitations in this paper. Nevertheless, it is open for future research.

Finally, the distribution of returns can be problematic, since it does not follow a normal distribution. Which is one of the assumptions for the one-sample t-test performed in this research. One alternative for samples that do not follow a normal distribution, is the Wilcoxon singed-rank test (Wilcoxon, 1945). The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used to determine whether the population mean ranks differ between two related samples. This non-parametric test counts the amount of negative and positive differences to determine whether two dependent samples have the same distribution. Because this test sums the ranks, it can lead to different conclusions for sample means that are heavily skewed. Below, the equation for the Wilcoxon signed-rank test is shown.

$$W = \sum_{i=1}^{N_r} [sgn(x_{2,i} - x_{1,i}) * R_i] \tag{8}$$

Where, W is the test statistic, N_r the sample size, sgn the sign function, $x_{2,i}$ *and* $x_{1,i}$ the corresponding ranked pairs from the two distributions and R_i is the rank. The null hypothesis for this test is that medians of the two samples are equal. This test is done by using Stata and it confirms the research question when the z-statistic is positive and significant for a 5%-significance level.

5.2 GSCORE

At the beginning of this research, the paper of Mohanram (2005) was introduced as a fundament to base this paper on. Thereafter, the reasoning behind the deviation from certain signals was substantiated based on the literature on technology stocks. To test the validity of these deviations the GSCORE (used by Mohanram) is replicated. In appendix figure 4, the signals contributing to the GSCORE are shown. There are 4 differences with the GASCORE. First, the return over assets (ROA) is replaced by the asset turnover. Second, the CFO which is bigger than the net income is replaced by the CFO minus the net income. Which returns a signal of 1 in case it is larger than the cross-sectional median. Furthermore, the capital expenditures are replaced by a signal based on the analyst consensus. At last, the advertisement expenditures are substituted for a signal based on ROIC. The last two deviations together with the R&D expenses created a threesome of signals that proxies the growth opportunities of stocks. In the GSCORE, the last bucket of signals (figure 4) is a proxy for the accounting conservatism of a company's financial statement. For the GASCORE, the last bucket is made from signals that indicates the amount of option value. The reason for this deviation is substantiated in section 3.4. There is no look-ahead bias as the signals were positive and significant in the previous literature (Mohanram, 2015).

To measure the ability of the GASCORE to pick outperformers in the technology sector it is compared to the GSCORE, which is a more general score performed on low book-to-market firms. To determine this, the mean returns for the highest scores are compared. This is done by subtracting the returns of the highest GSCORE from the highest GASCORE. Thereby, answering the following hypothesis.

$$H_0: \textit{The return of the highest GASCORE minus the return of the highest GSCORE}$$
$$\textit{is equal or smaller than zero}$$

The null hypothesis will be rejected when the difference is bigger than zero for a 5% significance level. This is tested by using a two-sample t-test (7). This test is important to determine whether the deviations from the previous GSCORE are justified. Only determining whether the GASCORE can outperform the whole sample (as explained in GASCORE 5.1), is not necessarily a justification from the deviation of signals from prior literature.

5.3 GASCORE* and GASCORE**

To determine whether the returns are robust after controlling for the anomalies found by Fama and French (1992; 2015), two additional scores are created. First, the GASCORE*, which is the GASCORE adjusted for the Fama an French 3-factor model (Fama & French, 1992). This is done by taking the yearly returns and subtracting the risk-free rates from it, which is obtained from the Fama and French website (French, 2021). Thereafter, the yearly returns of the different portfolios of GASCORES are regressed against the three yearly factors from the Fama and French website (French, 2021). The three factors that are regressed against the returns are the excess return on the market $(r_M - r_f)$, the size factor (SMB), and the value factor (HML). By regressing the return against the different factors, the Beta's are obtained that are used to determine the cost of equity. The β_1, following from the regression of the excess return on the market, is multiplied by the average values of these factors over the years 1998 until 2018. Ceteris paribus, the β_2 (SMB) and β_3 (HML) are multiplied by the averages of the two factors. Afterward, the values are summed up to get the cost of equity. The cost of equity is subtracted from the yearly returns of the different portfolios, which leads to the creation of the GASCORE*. To determine whether the GASCORE* is still able to pick outperformers in the technology sector after controlling for the anomalies found in the literature, a one-sample t-test (5) is performed on the highest GASCORE*.

The GASCORE** is determined using the same method as the GASCORE*. The only deviation is that the Fama and French 5-factor model, from which this score is derived, uses 5 factors instead of 3. Thereby, also regressing the returns of the different GASCORE portfolios against the profitability (RMW) and investing (CMA) anomalies (Fama & French, 1992), to see whether the returns are still robust. It is interesting to see if, and in which way, the cost of equity is changing by adding the two factors. To determine whether the two scores are outperforming the whole sample the following two hypotheses are tested.

H_0: *The difference between the GASCORE* and the whole sample is equal to or smaller than zero.*

H_0: *The difference between the GASCORE** and the whole sample is equal to or smaller than zero.*

The null hypotheses will be tested against a significance level of 5%. The one-sided simple t-test will give a better understanding of the robustness of the results. When the hypothesis in 5.1 is positive and significant but the null hypotheses of the GASCORE* and the GASCORE** cannot be rejected, the ability to outperform using the GASCORE is highly doubtful.

6. Results

In the following section, the results of the different scores and tests are shown. First, the validity of the chosen signals is tested by performing a two-sample t-test in section 6.1. Secondly, the ability of the GASCORE to pick outperformers in the technology sector is analysed in chapter 6.2. Furthermore, in section 6.3 the return of the GASCORE is compared to the GSCORE to determine whether the deviation from the previous signals is justifiable. At last, the robustness of the GASCORE is measured by adjusting for the Fama and French 3 and 5-factor models in chapter 6.4.

6.1 Testing the signals

To understand the effectiveness of the individual signals, the relationship between the individual signals and the sample is being analyzed. This is especially important for this research to justify the deviation from previous literature on low book-to-market companies (Mohanram, 2005). The mean returns of the companies that met the criteria (1) are compared to the mean returns of firms that did not meet the criteria (0). The average yearly returns of a portfolio composed of companies with the binary score of 0 are subtracted from a portfolio that consists of companies with the binary score of 1. Afterward, a two-sample t-test is performed on this mean difference. As shown by the results (Table 4), five of the eight signals are positive and significant for a 5%-significance level. Implying that they can separate companies with higher one-year returns from companies with lower returns. Of the five signals that are positive and significant, four are deviations from the previous GSCORE (Mohanram, 2005). This is a primary confirmation that the deviation is logical. The full validity will be tested more in depth when the GASCORE and GSCORE are compared in section 6.3.

The two signals on earnings and revenue growth variability, that were the basis of naive extrapolation (GA4 & GA5), are both not significant. Suggesting that, within our sample of technology companies, investors do not value companies with low variance in the sales and net income. This is explainable by the characteristics of the technology companies. These are, especially in the early stage, characterized by explosive growth (Loomis & Taylor, 2012). The expectation was that despite these characteristics, investors would still value companies with low variance. Based on these results, this expectation does not hold. Moreover, companies that are separated on the weighted research and development expenses have a lower return. For the sample of technology stocks, the relatively high (adjusted by revenue) amount of R&D expenses was expected to be crucial for signaling future growth and the long-term orientation of companies (Lantz, 2005; Flammer & Bansal, 2017). Despite this, companies with relatively higher R&D expenses are associated with lower returns. This can be an indication that it is hard to translate expenses in research and development into profitable investment opportunities. Moreover, R&D expenses may be translated into profits after a multiple-year time period as it takes time to exploit it. Therefore, additional research is required on this topic.

The biggest absolute difference between the mean return of the signals comes from the analyst recommendations. The literature was ambiguous on this topic, as the efficient market hypothesis and the empirical evidence was contradicting the outperformance based on analyst recommendations (Baker & Dumont 2014; Malkiel, 1989). The positive and significant t-statistic of 4.80*** indicates that there is a rationale behind adding analyst recommendations to the previous scores that were only performed on financial statement analysis (Piotroski, 2000; Mohanram, 2005). In addition, the signal based on the difference between CFROA and NI is also positive and significant (2.29**). Therefore, it is a possible improvement of the third signal in the GSCORE of Mohanram (2005). The GSCORE took a signal in which the CFROA should be bigger than the ROA, but this was negative and significant. Moreover, by replicating the GSCORE, this signal returned a score of 1 for nearly all the companies in the sample. This is because this signal within the GSCORE was not compared to a sample median, but it only looked at whether the CFO is bigger than the net income. Therefore, there is little added value from adding such a signal.

By having determined the meaningfulness of the individual signals the GASCORE can be created. The GASCORE is determined by taking the sum of all the individual signals. The advantage of this method of stock picking is that it is easy to use, and it takes several signals into account. This is an improvement of investing techniques based on single signals like a P/E ratio. In addition, the different signals can reinforce each other as companies with high asset turnover and favourable analyst recommendations may have a higher probability of outperformance. Especially, given the low correlation of the signals as shown in the data section. The disadvantage of this method is that given the wide range of financial statement items there are several ways in which to conduct a similar score with a slightly different item. Therefore, the rationale behind the chosen signal may be ambiguous.

Table 4. Relation between the 1-year returns of the individual GA signals

Variables	0			1				
	Count	Mean	Standard Deviation	Count	Mean	Standard Deviation	(1) - (0)	t-statistic
GA 1: Asset turnover > Median	5917	17%	0,45	5897	24%	0,37	6,69%	1.99**
GA 2: CFROA > Median	5998	14%	0,49	6017	30%	0,39	16,35%	4.64***
GA 3: CFROA - NI > Median	6041	17%	0,36	6039	27%	0,51	9,27%	2.29**
GA 4: Earnings variability < Median	5441	23%	0,47	5439	22%	0,38	-1,28%	(0.46)
GA 5: Revenue growth variability < Median	5403	23%	0,48	5401	23%	0,37	-0,03%	(0.02)
GA 6: R&D expenses > Median	4913	26%	0,43	4927	20%	0,49	-6,40%	(3,06)***
GA 7: Analyst recommendations > Median	4692	14%	0,41	4891	31%	0,46	17,51%	4.80***
GA 8: ROIC > Median	5081	16%	0,45	5061	29%	0,39	12,73%	3.49***

The table above represents the 1-year returns for the two binary values for the sample of 1504 technology stocks. The t-values are determined by using a two-sample t-test. */**/*** represent the significance levels of the two tailed test with 10%/5%/1% levels, respectively).

6.2 Picking outperformers with the GASCORE

In the following section, the main research question will be answered whether the GASCORE is able to pick outperformers among U.S. Listed technology companies. In the table below, the results of the different GASCORE are displayed. The GASCORE of zero and one, and seven and eight are combined since the count of the separate scores would be too low for a proper analysis. This is due to the low correlation of the individual signals. Moreover, the whole sample is added to compare the different mean returns of the GASCORES. To compare the results, two benchmarks are added, these are the S&P 500 and the NYSE Archa Tech 100. The S&P 500 as a proxy for the whole market and the NYSE Archa Tech 100 ("NYSE") to resemble the returns in the U.S. technology sector. The high difference between the mean return of the whole sample compared to the NYSE is due to yearly rebalancing and the skewness of the returns as explained in the data section. Furthermore, the whole sample consists of more companies with low market capitalization which could explain the higher return (Fama & French, 1995). Despite the higher return, the Sharpe ratio is comparable for the whole sample and the technology index benchmark. In addition, the technology sector did outperform the whole market on an absolute basis and also after controlling for yearly portfolio variance (0.47>0.35; 15.3%>7.9%).

To determine whether the GASCORE can pick outperformers in the technology sector, a one-sample t-test is performed over the mean of the whole sample. The null hypothesis tests whether the difference between the whole sample and the highest GASCORE is equal to or smaller than zero. The t-statistic for this test is 4.07*** ($p<0.05$) and therefore positive and significant with a 5%-significance level. Therefore, the null hypothesis can be rejected that the difference is smaller or equal to zero, implying that the GASCORE is indeed able to pick outperformers in the technology sector. By looking at the returns of the other GASCORES, the highest score is also the score with the highest return. When the return is adjusted for the portfolio variance the GASCORE of 6 is outperforming the GASCORE of 7-8. Suggesting, that the GASCORE of 6 is the best performing portfolio on a risk-adjusted basis. Moreover, to test whether the GASCORE of 7-8 is still outperforming the whole sample a Wilcoxon singed-rank test is performed. This test does measure whether the medians of the two samples are different. As the returns are not normally distributed this test is used to empower the results. The yearly returns for the portfolios are compared with each other. In appendix Table 5, the results of the test are shown. The Z-value is equal to 3.1 which is bigger than the significant z-value of 1.96 (given 5%-significance level). Therefore, the Wilcoxon singed-rank test enforced the conclusion that the GASCORE can pick outperformers.

By looking at the standard deviation, the GASCORE of 7-8 has the second-lowest standard deviation just after the GASCORE of 6. This is surprising because stock portfolios with more companies in them are normally associated with smaller variations in returns (Merton, 1972). Despite this, the portfolio consisting of the GASCORES of 7-8 (308), has a lower variance of returns than the GASCORE of 4, even though it has 2978 counts (0.48 > 0.39). Implying that the companies with the highest score have a lower variance of returns. This was also the expectation as the GASCORE is trying to separate "bad" companies from the more fundamentally "strong" firms. Furthermore, the t-statistics of the companies with a score from 0 to 3 are all negative and significant. This indicates that the GASCORE can also identify worse-performing stocks and therefore a long-short portfolio may be suitable. The GASCORE of 4 appears to be positive and significant even though the expectation for a higher or lower return than the whole sample was ambiguous. At last, the GASCORES of 5-8 are all positive and significant. Suggesting, that there are multiple GASCORES that outperformed a strategy by investing in the whole sample.

Table 6. Return on investment strategy based on GASCORE

GASCORE	N	Return	Standard Deviation	Sharpe Ratio	T-test
Whole Sample	12101	22,0%	0,43	0,47	
S&P 500		7,9%	0,17	0,35	
NYSE Archa Tech 100 Index		15,3%	0,28	0,47	
GASCORE: 0-1	977	6,7%	0,49	0,10	(3.75)***
GASCORE: 2	1939	11,1%	0,47	0,19	(3.09)***
GASCORE: 3	2749	18,7%	0,44	0,38	(2.47)***
GASCORE: 4	2978	25,8%	0,48	0,50	1,47
GASCORE: 5	2136	30,6%	0,41	0,70	3.07***
GASCORE: 6	1014	34,1%	0,31	1,04	2.97***
GASCORE: 7-8	308	38,5%	0,39	0,93	4.07***

The table above represents the 1-year returns for the two binary values for the sample of 1504 technology stocks. The t-values are determined by using a one-sample t-test. */**/*** represent the significance levels of the single tailed test with 10%/5%/1% levels, respectively. The GASCORES from 0-3 are tested for negative differences from the whole sample while the GASCORES from 5-8 are tested for positive values. For GASCORE 4 a two-tailed test is performed, as the it is ambiguous whether the outcome should be positive or negative.

To determine whether the GASCORE can identify outperformers from losers the different scores are compared with each other. First, the portfolio of GASCORES of seven and eight is subtracted from the GASCORES of zero and one to determine whether the difference is significantly higher than zero. If only this difference is significantly higher than zero, then there is little evidence that the GASCORE can separate outperformers from losers. Afterwards the scores of six and two are compared. If this is test is also positive and significant, there is moderate evidence that the GASCORE can separate outperformers. At last, the scores that have the lowest difference (three and five) are compared. If this score is still positive and significant, the GASCORE is highly capable of separating outperformers from losers.

The tested null hypothesis thereby is that the difference between the two GASCORES is equal to or smaller than zero. In the Table below the t-statistics are presented. For all the mean return differences, the GASCORE is positive and highly significant. The GASCORES with the largest score difference has a t-statistic of 4.39*** ($p<0.05$), suggesting, that there is a high ability to separate outperformers from losers. Moreover, the GASCORE of six minus two has a t-statistic of 3.59*** ($p<0.05$), implying an even higher ability to separate winners from losers. At last, to determine whether the GASCORE has a high ability to separate winners from losers, the GASCORES of five and three are compared. As shown in Table 7, the t-statistic is 2.96*** (p<0.05), which signifies the difference to be positive and significant.

It is interesting to see, that the higher the difference is between the GASCORES the bigger the difference in mean returns. For instance, the GASCORES of six and two are more separate from each other than scores of five and three. The returns follow the same pattern by also having larger differences. The outcomes in this research are compared to the result of Mohanram (2005). He found a difference between the GSCORE of 0, and the GSCORE of 8, of 29.5% (31.8% in this research). A difference between our result and the outcomes from the GSCORE performed by Mohanram (2005), is that the portfolios of low book-to-market scores had a negative mean returns while for our sample all the returns are positive. This can be explained by the narrow sample of technology companies that were one of the best performing sectors in the U.S. (Mensi et al., 2021). In chart 6 of the appendix, the differences between the closest GSCORE and GASCORE are displayed. For example, the score of 2 is subtracted from the score of 3 to understand the relationship between adding a binary value of 1 to the score. For both scores, an increase is associated with a higher return. There is no score for which the return decreases from an additional positive signal. In the following section, the relationship between the GASCORE and GSCORE will be further investigated.

Table 7. Mean differences high vs low GASCORES

GASCORE	N	Return	Standard Deviation	-	N	Return	Standard Deviation	Return Difference	T-test
GASCORE: 7/8 - 0/1	308	38,5%	0,39		977	6,7%	0,49	31,8%	4.39***
GASCORE: 6 - 2	1014	34,1%	0,31		1939	11,1%	0,47	23,0%	3.59***
GASCORE: 5 - 3	2136	30,6%	0,41		2749	18,7%	0,44	11,9%	2.96***

The table above represents the 1-year mean returns for the different GASCORES for the sample of 1504 technology stocks. The t-values are determined by using a two-sample t-test on the return differences of the different GASCORES. */**/*** represent the significance levels of the two tailed test with 10%/5%/1% levels, respectively.

6.3 GASCORE vs GSCORE

In the subsequent paragraph, the effectiveness of the GASCORE is compared to the GSCORE (Mohanram, 2005). In this paper, multiple explanations are given to deviate from the previous literature (see the research design). To be able to compare to two scores, the GSCORE needs to be replicated for the sample of technology stocks. This is done in Table 8. By looking at the mean returns there seem to be less variation between the different GSCORES. Especially the GSCORE of 0/1 is even higher than the return of the whole sample. Furthermore, the t-statistic is also less consistent compared to the GASCORE. Nevertheless, the Sharpe ratio is increasing with the higher GSCORE due to having lower variance. Suggesting that, the higher GSCORE picks more fundamentally strong companies with lower stock variance.

Table 8. Return on investment strategy based on GSCORE

GASCORE	N	Return	Standard Deviation	Sharpe Ratio	T-statistic
Whole Sample	12099	22,1%	0,44	0,46	
S&P 500		7,9%	0,17	0,35	
NYSE Archa Tech 100 Index		15,3%	0,28	0,47	
GASCORE: 0-1	476	25,2%	0,76	0,31	0.86
GASCORE: 2	1184	21,6%	0,70	0,28	(0.08)
GASCORE: 3	2195	17,3%	0,49	0,31	(2.17)**
GASCORE: 4	2477	20,8%	0,45	0,42	(0.78)
GASCORE: 5	2112	24,2%	0,37	0,60	0.91
GASCORE: 6	1769	25,0%	0,35	0,66	1.34
GASCORE: 7-8	1886	23,1%	0,33	0,63	0.29

The table above represents the 1-year returns for the two binary values for the sample of 1504 technology stocks. The t-values are determined by using a one-sample t-test. */**/*** represent the significance levels of the single tailed test with 10%/5%/1% levels, respectively. The GSCORES from 0-3 are tested for negative differences from the whole sample while the GSCORES from 5-8 are tested for positive values. For GASCORE 4 a two-tailed test is performed, as the it is ambiguous whether the outcome should be positive or negative.

After having replicated the GSCORE, the two scores are compared. This is done in Table 9. To answer whether the GASCORE is more capable of identifying outperformers among U.S. listed technology companies than the GSCORE, the following null hypothesis is tested. The highest GASCORE minus the highest GSCORE is equal to or smaller than zero. As shown in the Table, the t-statistic is 3.84*** ($p<0.05$), which is highly positive and significant. Implying that the difference of 15.3% between the two scores is significantly higher than zero and thereby rejecting the null hypothesis. This enforces the validity of the research to deviate from the previous signals used in the GASCORE. Thereby, creating a more specific multiple-signals-based approach for the technology sector. Moreover, it also adds evidence to the literature for more industry-specific signals. Due to the signals in the GSCORE, the count of the score 7/8 is much higher than the GASCORE. The reason for this is that the third signal (G3) (see appendix figure 4), is positive for nearly all the companies in the sample. Therefore, to have two buckets of returns that are more similar to each other the score 7/8 is split into two categories.

Table 9. Difference between the GSCORE and GASCORE returns

	GSCORE			GASCORE			GASCORE - GSCORE	
	Return	Count	Standard Deviation	Return	Count	Standard Deviation	Return Difference	T-statistic
Score: 0/1	25,2%	476	0,76	6,7%	977	0,49	-18,5%	(2.44)***
Score: 2	21,6%	1184	0,70	11,1%	1939	0,47	-10,5%	(2.11)**
Score: 3	17,3%	2195	0,49	18,7%	2749	0,44	1,4%	0.10
Score: 4	20,8%	2477	0,45	25,8%	2978	0,48		
Score: 5	24,2%	2112	0,37	30,6%	2136	0,41	6,4%	0.84
Score: 6	25,0%	1769	0,35	34,1%	1014	0,31	9,0%	2.94***
Score: 7/8	23,1%	1886	0,33	38,5%	308	0,39	15,3%	3.84***

In table 5, the ability of picking outperformers and underperformers by using the GASCORE and GSCORE are compared. This is done by performing a two-sample t-test. As the GASCORE is more specific on the technology sector, the expectation is that it is better at dividing winners from losers. Therefore, for the scores from 0-3, the expectation is that the returns are lower for the GASCORE than the GSCORE. Moreover, the scores from 5-8 are expected to get a higher return for the GASCORE. The score of 4 is left out as it is ambiguous whether this score should be positive or negative. The t-values are determined by using a two-sample t-test. */**/*** represent the significance of the single tailed test with 10%/5%/1% levels, respectively.

In Table 10 within the appendix, the GSCORE is split into 9 individual scores. As shown, the count is more comparable after this adjustment. To test whether the GASCORE is still better at picking outperformers, a two-sample t-test is done. In the table below, the result of this statistical test is shown. By splitting the GSCORE into individual scores, a higher return is seen for the score of 8. By comparing this score to the GASCORE of 7/8, the difference is tested against zero. As presented, the t-statistic is 2.09** ($p<0.05$), which is (again) positive and significant. Therefore, the null hypothesis can be rejected. The two tests show that the GASCORE is capable of picking outperformers better than the GSCORE. This is an interesting conclusion, as adding signals that are substantiated within the literature improves the performance of scores. In addition, the deviation from a score solely performed on financial statements by adding analyst recommendations also appears to be logical. The disadvantage of this is that the broad universe of possible signals makes it hard to justify the validity of certain signals.

Table 11. Difference between the GSCORE and GASCORE returns

GSCORE 8			GASCORE 7/8			GASCORE - GSCORE	
Return	Count	Standard Deviation	Return	Count	Standard Deviation	Return Difference	T-test
28,8%	321	0,52	38,5%	308	0,39	9,7%	2,09**

In table x, the ability of picking outperformers and underperformers by using the GASCORE and GSCORE are compared. As the GASCORE is more specific on the technology sector, the expectation is that it is better at dividing winners from losers. The scores of 7/8 are expected to get a higher return for the GASCORE than the GSCORE of 8. The GSCORE is split up to have a more comparable amount of observations. The t-values are determined by using a two-sample t-test. */**/*** represent the significance of the single tailed test with 10%/5%/1% levels, respectively.

6.4 GASCORE adjusted for the Fama and French factors

After having compared the GASCORE to the GSCORE, the subsequent section will identify whether the GASCORE is still able to pick outperformers after correcting for the anomalies found within the literature. Firstly, the GASCORE will be adjusted by the Fama and French 3-factor model (Fama & French, 1992). Thereby, creating the GASCORE* (Table 12). The cost of equity is the required return on the portfolio of stocks, this is estimated with a regression of the Fama and French factors against the yearly return of the portfolios. For instance, the whole sample has a cost of equity of 10.2%. This means that based on the portfolio variance this is the required return on the portfolio. The correction on the returns is made to decide whether the portfolios are not only separating the stocks based on certain anomalies, but to see whether there is an actual alpha. By looking at the cost of equity, there appears to be a decreasing relationship with the GASCORE. The highest GASCORE does not only have the highest return after controlling for the market risk premium, the size premium, and the value premium. It also has a lower cost of equity than the whole sample and second-lowest of all the GASCORES. Suggesting that, based on the volatility of the portfolio it has a lower required return compared to the whole sample.

To determine whether the GASCORE can separate outperformers among U.S. Listed technology companies after correcting for Fama & French 3-factor model, a simple t-test is performed. Thereby testing whether, the difference between the GASCORE* and the whole sample is equal to or smaller than zero. The null hypothesis is rejected as the t-statistic is 2.79*** ($p<0.05$), which is highly positive and significant. The other adjusted scores do not deviate too extensively from the GASCORE, since the t-values are comparable. The scores of 0-3 are all still negative and significant and the values from 4-8, remain positive and significant. Moreover, the GASCORE of 0/1 appears to be negative after correcting for the Fama and French 3-factor model. Suggesting that, after controlling for the factors, there is a negative alpha.

Table 12. Return on GASCORE* corrected for Fama and French 3-factor model

GASCORE	N	Return	Standard Deviation	Cost of Equity	T-test
Whole Sample	12101	11,9%	0,44	10,2%	
GASCORE: 0/1	977	-4,8%	0,53	11,4%	(3.87)***
GASCORE: 2	1939	0,4%	0,47	10,6%	(3.27)***
GASCORE: 3	2749	7,8%	0,45	11,4%	(2.05)**
GASCORE: 4	2978	15,5%	0,48	10,3%	1,08
GASCORE: 5	2136	20,5%	0,41	10,0%	2,68***
GASCORE: 6	1014	27,1%	0,31	7,0%	2.71***
GASCORE: 7/8	308	30,1%	0,39	8,3%	2.79***

The table above represents the 1-year adjusted returns for the two binary values for the sample of 1504 technology stocks. The average yearly returns are adjusted for the size premium (SMB)and the value premium (HML).The t-values are determined by using a one-sample t-test. */**/*** represent the significance levels of the single tailed test with 10%/5%/1% levels, respectively. The GASCORES* from 0-3 are tested for negative differences from the whole sample while the GASCORES* from 5-8 are tested for positive values. For GASCORE* 4 a two-tailed test is performed, as the it is ambiguous whether the outcome should be positive or negative.

After having formed the Fama and French 3-factors model, which was an expansion of the CAPM model (Fama & French, 1992). Fama and French (2015) added two additional factors, RMW and CMA. That was derived from the profitability of companies and their investment behaviour. After having adjusted the returns with the 5-factor model, the GASCORE** is created. The results are shown in the Table below. The cost of equity for the whole sample is lower than for the 3-factor model (10.2%>2.0%). Implying that, based on the variance of the full sample, the required return is lower by including the additional factors. The GASCORE of 7/8 instead of having a low cost of equity compared to the other portfolios, now has the highest cost of equity of all the portfolios. Suggesting that, adding the additional factors, results in a higher required return on the portfolio of companies with the highest GASCORE. By looking at these results, it appears that the GASCORE is picking outperformers but that part of it is also explained by the anomalies in the literature. To test whether there is still an alpha by investing in the highest GASCORE the research goal will be answered with a simple t-test. The GASCORE can separate outperformers from losers among U.S. Listed technology companies after correcting for Fama & French 5-factor model. Thereby testing the null hypothesis whether, the difference between the GASCORE* and the whole sample is equal to or smaller than zero. The t-value is 2.66*** (p<0.05) which is positive and significant. This means that after controlling for the factors that outperform within the literature the GASCORE is still able to pick outperformers among U.S. technology companies.

Table 13. Return on GASCORE** corrected for Fama & French 5-factor model

GASCORE	N	Return	Standard Deviation	Cost of Equity	T-test
Whole Sample	12101	20,2%	0,43933	2,0%	
GASCORE: 0-1	977	6,3%	0,52929	0,2%	(2.52)***
GASCORE: 2	1939	9,3%	0,47311	1,8%	(2.31)**
GASCORE: 3	2749	14,8%	0,45296	4,4%	(1.98)**
GASCORE: 4	2978	24,4%	0,48161	1,4%	0.96
GASCORE: 5	2136	27,9%	0,40951	2,7%	1.87**
GASCORE: 6	1014	29,1%	0,30839	4,9%	2.39***
GASCORE: 7-8	308	32,4%	0,39488	6,1%	2.66***

The table above represents the 1-year returns for the two binary values for the sample of 1504 technology stocks. The t-values are determined by using a one-sample t-test. */**/*** represent the significance levels of the single tailed test with 10%/5%/1% levels, respectively. The GASCORES** from 0-3 are tested for negative differences from the whole sample while the GASCORES** from 5-8 are tested for positive values. For GASCORE** 4 a two-tailed test is performed, as the it is ambiguous whether the outcome should be positive or negative.

7. Conclusion

This research aimed to determine whether the GASCORE can pick outperformers among U.S. Listed technology companies. Based on quantitative analysis on U.S. listed technology companies, it can be concluded that the multiple-signal-based approach is indeed able to identify outperformers. Both the one-sample t-test and the Wilcoxon signed-rank performed in this research were positive and significant. Indicating that the GASCORE is a useful tool for investors to pick outperformers in the technology sector. This was achieved by using signals based on financial statement analysis and analyst recommendations. Thereby, enhancing the academic literature on the value of fundamental analysis. Moreover, the individual signals also serve as a useful tool for managers of technology stocks to understand what financial statement items drive value. Furthermore, this paper researched whether the GASCORE can separate outperformers from losers. The results showed that the GASCORES with a low value was significantly lower than the whole sample means. This provides the possibility of constructing a long-short portfolio to exploit this approach. For both research questions, the returns were highly positive and significant. Nonetheless, the bid-ask spread, and transactions costs involved in yearly portfolio rebalancing were not considered. This can be costly which decreases the returns of this strategy. As the determination of the exact magnitude of these costs lays beyond the scope of this research, it can be analyzed in future research. Moreover, the sample uses a timeframe in which the dot-com bubble was included, which skews the distribution of returns. These returns have a significant impact on the overall returns of the portfolios and may influence the effectiveness of this score in the future.

The GASCORE was partly derived from an earlier study conducted by Mohanram (2005). The GSCORE created in this research was similarly based on a multiple-signal-based approach. To make it more specific for the technology sector, this paper deviated from four signals. To add a consensus estimate of the different companies, this paper deviated from a sole financial statement analysis by adding analyst recommendations. The effectiveness of analyst recommendations was debated within the literature (Hong & Kacperczyk, 2010; Da & Schaumburg, 2011). Despite this, the findings suggested that analyst recommendations can segregate the sample into better and worse performing groups. To test the effectiveness of these deviations, the GSCORE was replicated and tested against the GASCORE. The results of these tests were positive and highly significant. Implying that the GASCORE is more capable of identifying outperformers among U.S. listed technology companies. This added meaning to the academic literature to have more specific signals for different sectors. Therefore, further research should consider more specific signals when trying to pick outperformers in sectors. Overall, this research added evidence for the effectiveness of a multiple-signal-based approach that can be used for investment decisions. Moreover, to decide whether the GASCORE can pick outperformance after correcting for anomalies found in the previous literature, the returns were adjusted for the Fama and French 3 and 5-factor models. This robustness check did not change the conclusion of the paper. For both the Fama and French models, the GASCORE is still able to outperform the overall technology sector.

7.1 Limitations

Identifying research limitations is important to determine to which extent the outcomes are representative of the total population of technology stocks. In addition, it helps to understand the practicality of the exploitation of the GASCORE with real-life limitations. Furthermore, it can help to determine improvements that can be researched in future literature. There are four main limitations that this research encountered.

The first limitation of this research is that companies classified as technology companies in a certain year are not necessarily classified under technology for the whole timeframe in the sample. For instance, company X may be considered in the sample as a technology company as of 2000, while Bloomberg only classifies this company as a technology company from 2007. This can result in; companies being added to the portfolio while they are not technology companies for a major part of the researched time horizon. The risk from this is that companies that were gaining market share and were outperforming eventually transformed into technology companies, and therefore the sample return can be higher. This is not expected to have large implications as the GASCORE tests the returns relative to the whole sample.

Secondly, the differences in the companies their filling dates make it difficult to build an investment strategy around the GASCORE. By determining the return of the GASCORE, this research assumes that immediately after the report is filled the decision to invest based on the GASCORE can be made. This is not true in practice. Before determining whether a company has a high or low GASCORE the information of all the other companies needs to be available. Therefore, investing based on this score is only possible after all the information is out, and it is impossible to immediately invest after the reports came out. A possible solution to tackle this issue is to estimate medians based on the expectations of stock analysts and adjust it after reports come out. As the median is taken for most signals, the expectations should not fluctuate too extensively from actual numbers. Furthermore, due to the yearly portfolio rebalancing, this strategy is looking more like an actively managed strategy than passive investing. As the report dates of companies are on different dates the buying and selling should happen frequently.

Third, the low count of the highest GASCORE can be problematic. This research is based on picking outperformers in the technology sector by looking at the returns of the highest GASCORE. Of all the yearly company returns only 308 were classified under this score. This means that of the twenty years within this sample this is true for only around 15 companies per year. Creating a well-diversified portfolio with no idiosyncratic risk is hard with such a low number. Therefore, an investment strategy that consists partly of companies with a lower GASCORE may be a suitable solution. Thereby, decreasing the overall return of the portfolio but increasing the number of investment possibilities.

Finally, the signals used in this research are subject to discussion. Despite that the signals used in this research were substantiated by academic literature, there are several possible deviations from these signals. As the financial statements consist of many items, the choice of the signals is ambiguous. Instead of using the signal based on return on invested capital or asset turnover the GASCORE could have easily deviated from one of these signals. Despite, the signals chosen in this research still managed to outperform the overall sample and were therefore useful. Especially for investors that want to have the first form of screening before digging into the financial statements this score can be valuable.

7.2 Recommendations for Future Research

After having discussed the limitations of this paper, the recommendations for future research will now be discussed. The small sample used here can be extended to broaden the literature on this topic of a multiple-signal-based approach.

First, the literature based on multiple signals can be elaborated for different sectors and countries. In this sample, the technology sector in the U.S. is used to determine the effectiveness of the score. One way in which additional literature can help to determine the validity of the GASCORE is to replicate the score for technology companies in different countries. For example, technology companies that are only listed on the European stock exchange can be analyzed. Moreover, this research performed a multiple-signal-based approach on a single sector. Other literature was focused on the whole horizon of low or high book-to-market firms (Piotroski, 2000; Mohanram, 2005). Therefore, more specific scores can be created on individual sectors. For instance, empirically substantiated signals for the healthcare sector can be tested to see whether it outperforms the whole market. Thereby, testing the result against the GASCORE and the GSCORE to determine the validity.

Secondly, additional research could determine a practical solution to implement the GASCORE. As discussed in the limitations, the reported date is problematic to apply the GASCORE for actual investing. Therefore, some minor adjustments can increase the practicality to exploit the outperformers or underperformance determined by the GASCORE. In addition, the costs for yearly rebalancing can be analyzed to determine for which amount of stock portfolio yearly rebalancing is profitable. Important is to consider both the transaction costs as the bid-ask spread.

At last, to determine the validity of the GASCORE, small deviations from the current signals can empower the score. As there are multiple possible signals that can be used in the multiple-signal-based approach, changing some factors can strengthen the effectiveness of the current model. Moreover, the new model could even perform better than the current GASCORE and thereby improve it. Furthermore, the GASCORE can also be tested in different industries to see whether it is still valid and thereby determining whether it can be used more broadly.

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Appendix

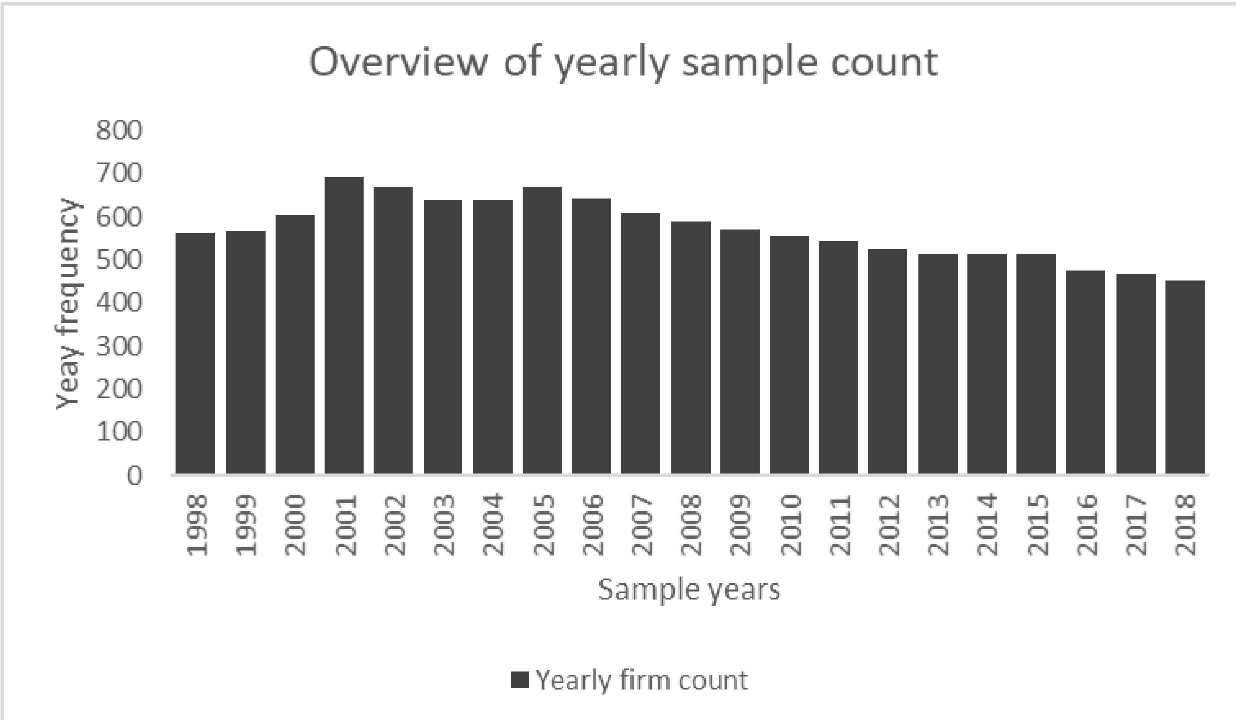

Chart 1: **Overview of the amount of firm counts per year of the sample of technology stocks**

JDS UNIPHASE CORPORATION

CONSOLIDATED STATEMENTS OF OPERATIONS
(IN MILLIONS, EXCEPT PER SHARE DATA)

	YEARS ENDED JUNE 30,		
	2001	2000	1999
Net sales	$ 3,232.8	$1,430.4	$ 282.8
Cost of sales	2,306.7	751.6	138.7
Gross profit	926.1	678.8	144.1
Operating expenses:			
Research and development	325.9	113.4	27.0
Selling, general and administrative	818.1	172.9	37.4
Amortization of purchased intangibles	5,387.0	896.9	15.7
Acquired in-process research and development	393.2	360.7	210.4
Reduction of goodwill and other long-lived assets	50,085.0	--	--
Restructuring charges	264.3	--	--
Merger and other costs	--	--	6.8
Total operating expenses	57,273.5	1,543.9	297.3
Loss from operations	(56,347.4)	(865.1)	(153.2)
Interest income, net	48.5	35.3	3.6
Gain on sale of subsidiary	1,770.2	--	--
Activity related to equity method investments	(883.9)	--	--
Loss on sale of available-for-sale investments	(559.1)	--	--
Reduction in fair value of available-for-sale investments	(522.1)	--	--
Loss before income taxes	(56,493.8)	(829.8)	(149.6)
Income tax expense (benefit)	(371.9)	74.9	21.5
Net loss	$(56,121.9)	$ (904.7)	$(171.1)
Basic and dilutive loss per share	$ (51.40)	$ (1.27)	$ (0.54)
Shares used in per share calculation:			
Basic and dilutive	1,091.9	710.9	318.2

See accompanying notes to consolidated financial statements.
50

Figure 2 Overview of the annual income statement of JDS UNIPHASE for 2001

Note. This financial statement gives an example of goodwill impairments after the crash of the dot-com bubble. For JDS Uniphase, the goodwill impairment in combination with the amortization of the intangibles resulted in a loss of more than 56 billion.

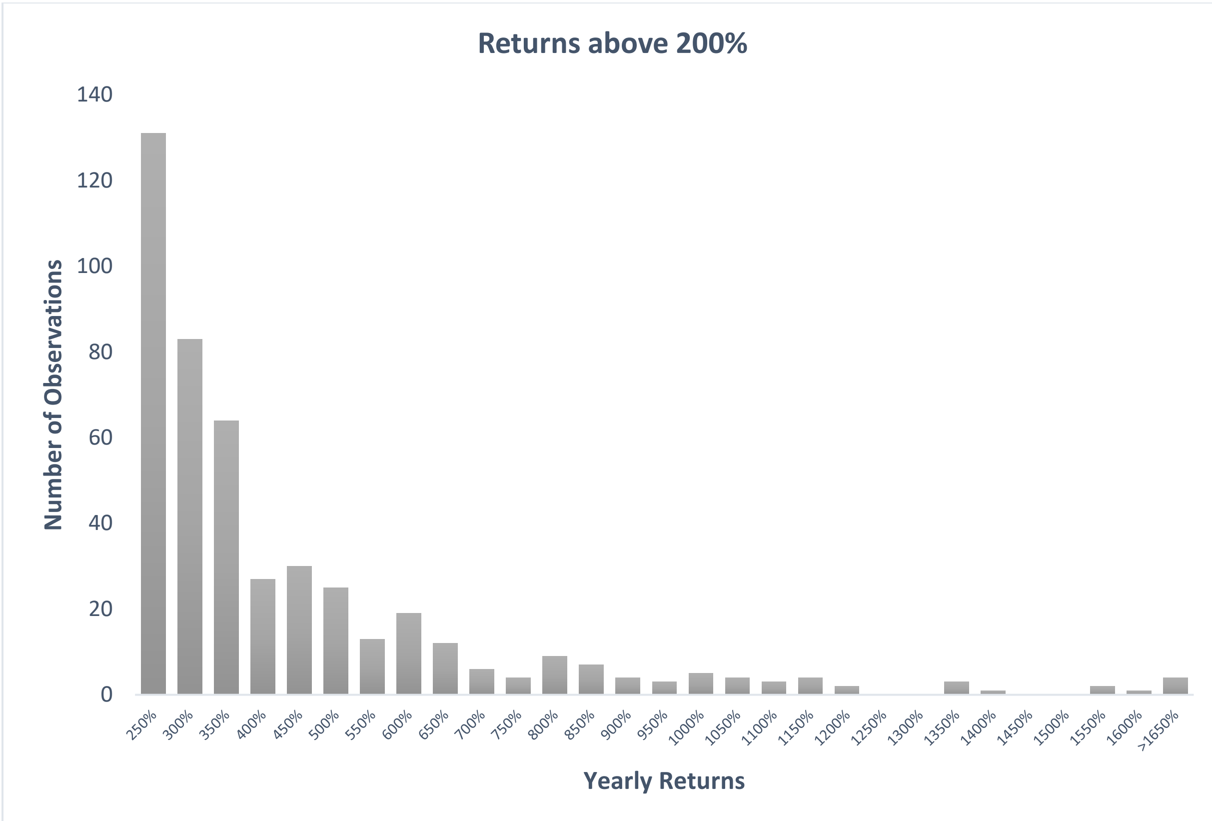

Chart 5: **Overview of the total shareholder returns above 200%**

Note. The chart with returns above 200% gives an indication in what extent the returns are positively skewed. Most of the values are around 300%. Nonetheless, there are 4 outliers in the sample with returns above 1650%.

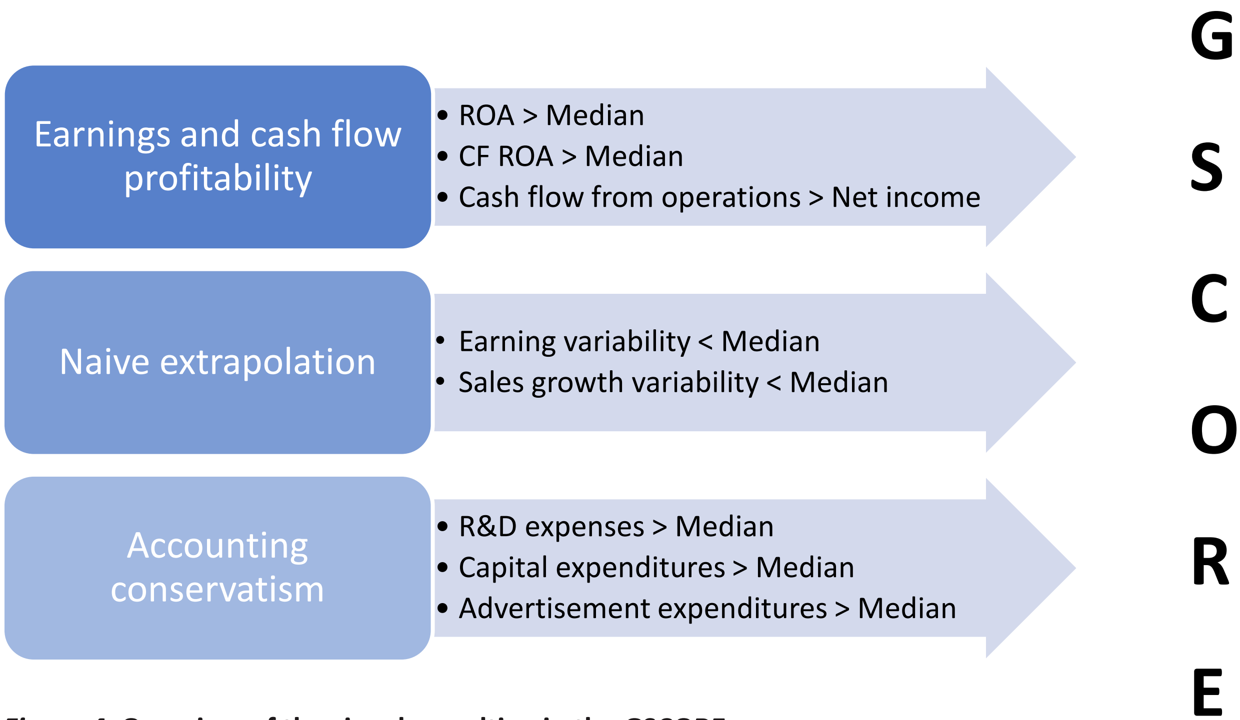

Figure 4: **Overview of the signals resulting in the GSCORE**

***Table 5:* Overview of the Wilcoxon singed-rank test between GASCORE 7-8 and the whole sample**

```
Wilcoxon signed-rank test

        sign |      obs   sum ranks    expected

-------------+---------------------------------

    positive |       17         205       115.5

    negative |        4          26       115.5

        zero |        0           0           0

-------------+---------------------------------

         all |       21         231         231


unadjusted variance      827.75

adjustment for ties        0.00

adjustment for zeros       0.00

                     ----------

adjusted variance        827.75


Ho: SCORE_7AND8 = WholeSample

             z =   3.111

    Prob > |z| =   0.0019
```

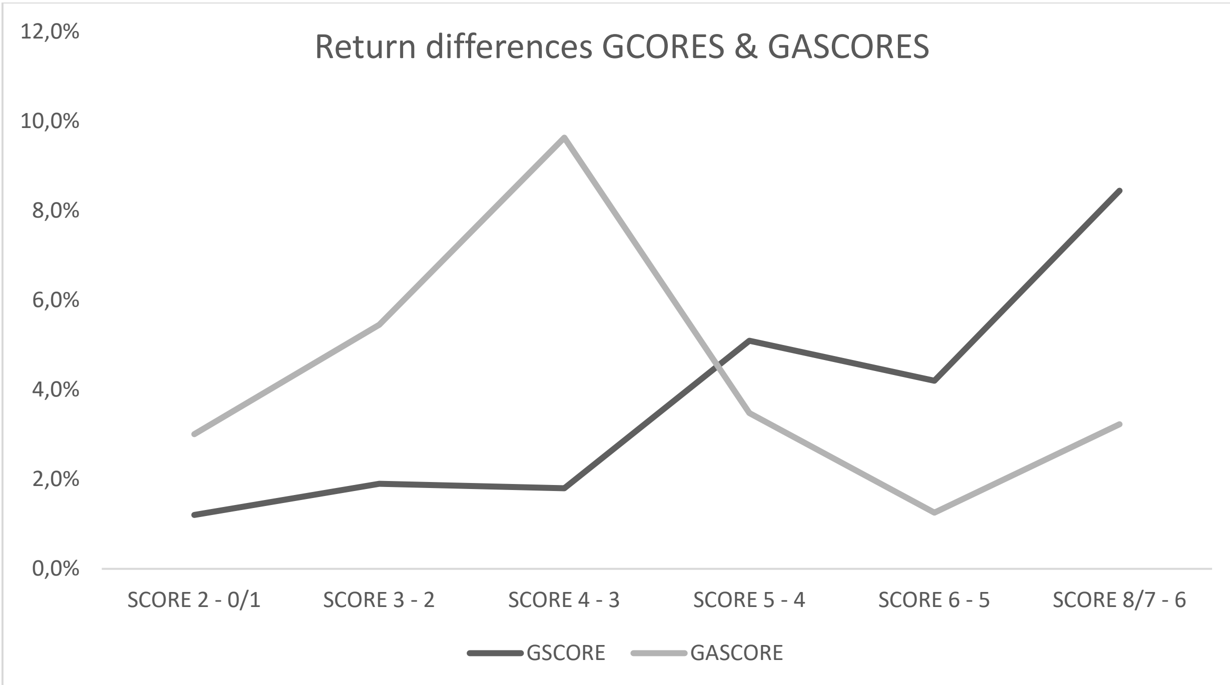

Chart 6: **Overview of the return differences between consecutive GSCORES and GASCORES**

Note. The difference between the consecutive G(A)SCORES is determined to understand the relationship between the different scores. As shown, all the values are positive. Implying that it is always better to invest in a higher score.

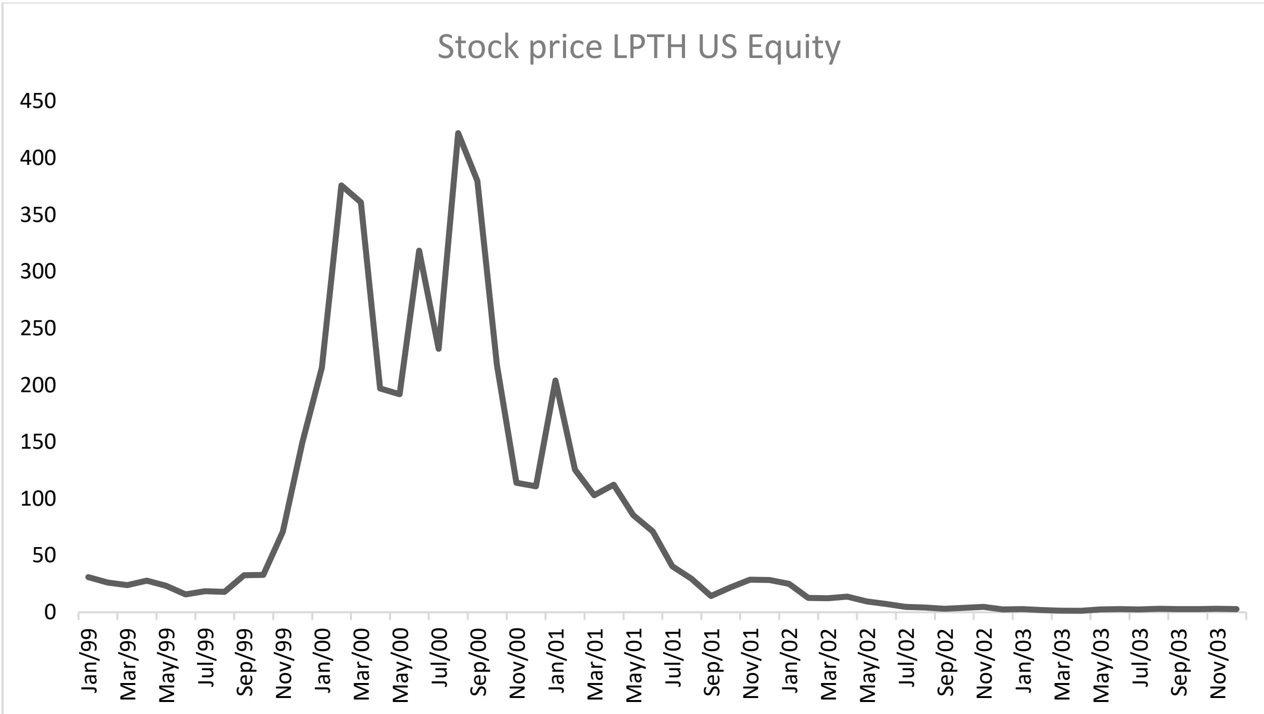

Chart 7: **Stock price of LPTH from 01/01/1999 until 03/11/2003**

Table 10. Return on investment strategy based on GSCORE without combined scores

GASCORE	N	Return	Standard Deviation	Sharpe Ratio	T-test
Whole Sample	12099	22,1%	0,44	0,46	
S&P 500		7,9%	0,17	0,35	
NYSE Archa Tech 100 Index		15,3%	0,28	0,47	
GASCORE: 0	91	12,0%	0,76	0,13	(2.44)***
GASCORE: 1	385	29,1%	0,85	0,32	1.74**
GASCORE: 2	1184	21,6%	0,70	0,28	(0.08)
GASCORE: 3	2195	17,3%	0,49	0,31	(2.17)**
GASCORE: 4	2477	20,8%	0,45	0,42	(0.78)
GASCORE: 5	2112	24,2%	0,37	0,60	0.91
GASCORE: 6	1769	25,0%	0,35	0,66	1.34
GASCORE: 7	1565	22,3%	0,73	0,28	0,04
GASCORE: 8	321	28,8%	0,52	0,52	1.71**

The table above represents the 1-year returns for the two binary values for the sample of 1504 technology stocks. The t-values are determined by using a one-sample t-test. */**/*** represent the significance levels of the single tailed test with 10%/5%/1% levels, respectively. The GSCORES from 0-3 are tested for negative differences from the whole sample while the GSCORES from 5-8 are tested for positive values. For GASCORE 4 a two-tailed test is performed, as the it is ambiguous whether the outcome should be positive or negative.