UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Factor investing in the technology sector

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Supervisor: Adam Farago

Authors:
Viktor Glimne
Walid Fayad

Abstract

This paper explores how well factor-based investing strategies do when applied to the technology sector, and how well they do against non-tech counterparts. It uses previous research into stock classification in order to select what stocks to include in the tech sample and the non-tech sample. From these, long-short portfolios are created to investigate the existence of abnormal returns and their eventual statistical significance. The differences between the tech and non-tech long-short portfolios are looked at, followed by the difference in risk-adjusted returns in the form of Sharpe ratios. The paper concludes that for three factors, there is no risk-adjusted advantage for either tech or non-tech stocks, and investors may choose tech for a higher risk and return profile or non-tech for lower risk but also lower return. For two factors, non-tech is found to be superior in terms of risk-adjusted returns, while tech is superior for one factor. Finally, one factor showed no significant differences in returns between tech and non-tech.

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Contents

1. Introduction

The main goal for the financial market participants is to maximize the risk-adjusted return. There are several strategies with various academic evidence that investors can rely on to identify undervalued securities or predict future asset prices. Although some consider it impossible to predict asset trends based on market data, many believe one can be able to predict asset trends and benefit from undervalued assets by using different investment strategies.

In accordance with the Efficient Market Hypothesis all financial assets are at all times priced accurately. This is due to all information constantly being available in the market and only new information can cause a change in the price of an asset. The Efficient Market Hypothesis therefore states that excess return in relation to the market is impossible to achieve unless the risk level increases (Fama, 1970). If the Efficient Market Hypothesis is valid, why do actors in the financial market use various investment strategies such as factor investing to gain excess returns compared to the market?

The purpose of this study is to examine factor investing as a trading strategy and study whether using this technique could give financial market participants an edge when investing in the technology sector. Previous research and statistics suggest that the tech sector could be one of the most, if not the most, important sectors for long time economic growth in countries with developed economies. Brown et al. (2017) found a positive link between initial tech sector size and productivity growth as well as GDP development. An important reason for this is the reliance of the tech industry on new research and development (R&D), four industries in the high-tech sector classified by a two digit SIC code being responsible for roughly 80% of spending on R&D among US corporations for the last 15 years.

Even though tech companies seem to be essential for scientific innovation and economic growth, there have historically been issues with investments into high tech companies compared to perhaps simpler, lower tech counterparts. There are a few problems, one of them being information asymmetry, considering that the scientific research made by high tech companies can be hard to explain to uninitiated investors, leading to it being harder to make informed decisions about financing them (Brown, Martinsson, & Petersen, 2017). There is also the issue of there being less collateral of absolute value in tech companies operating with a lot of R&D investments. Even so, at its core, equity financing could be a preferable way of financing a project of the risk profile a company with high R&D costs and an unsure but possibly large payoff.

This study hopes to add to the existing body of research into tech investments by researching how different factors affect the performance of tech firms. Essentially, it helps investors to make informed decisions when it comes to what tech firms to invest in, and test the performance of factor investing as a strategy for investing in the tech sector of the market, which investors could otherwise be hesitant to invest in.

1.1 Factor investing

A strategy known as factor investing refers to investing strategically in specific segments of the financial markets that offer better returns in the long run compared to those in other parts. This strategy emerged from the Capital Asset Pricing Model developed by William Sharpe (1964), John Lintner (1965a, b) and Jan Mossin (1966) in the early 1960s. Based on the Capital Asset Pricing Model, expected returns and market risks are linearly related. (Black, 1972). Introducing the CAPM made it theoretically possible to price investments as well as presenting a measurement regarding how an asset's market risk affects its return. Thus, the model accounted solely for beta, which is the market risk. Higher market risk, as determined by CAPM, should generate higher returns. Finding factors that can explain a given asset's risk and return characteristics, such as the market risk in CAPM, is in fact the key principle of factor investing (Centineo & Centineo, 2017).

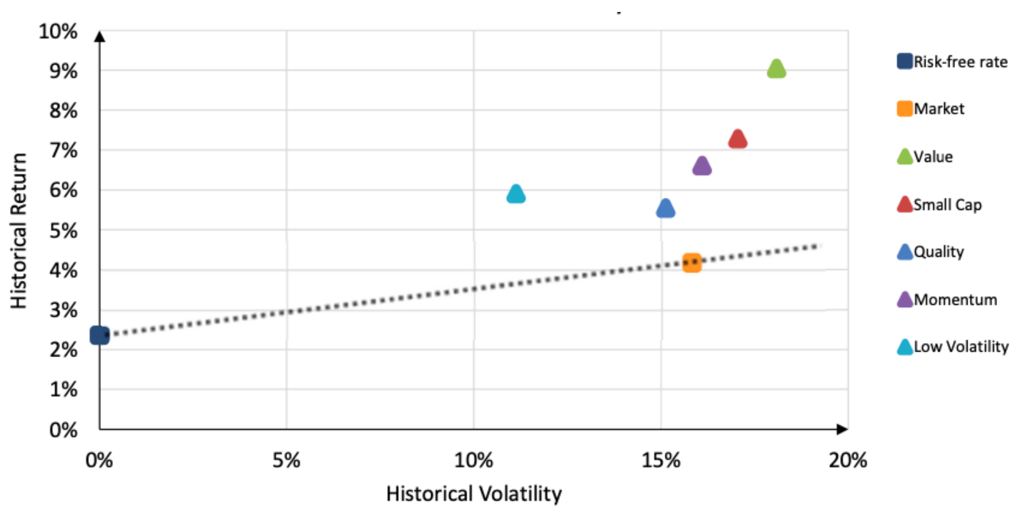

Figure 1. Graph illustrating historical return and volatility of the most common factors (Centineo & Centineo, 2017).

Factors are characteristics that are important in explaining the risk and return of securities. Portfolio performance of equity investments over the long run can be explained by a variety of factors. Several numbers of factors have historically been associated with long-run risk premiums as well as systematic sources of risk. The purpose of including factors in an investment strategy is to generate these risks and rewards. As illustrated in figure 1., Value, Low size, Low Volatility, High Yield, Quality and Momentum are the leading factors in generating higher risk-adjusted returns compared to an arbitrary portfolio (Centineo & Centineo, 2017). They are all established factors with solid explanations regarding their characteristics of generating a premium. Excess returns above market have been shown by empirical studies on these factors. Additionally, evidence also shows that factor investing accounts for much of the returns of mutual funds and institutional active funds (Bender et al, 2013).

It is possible to achieve abnormal returns when investing in the financial market, even though most markets are considered efficient. There have been several apparent anomalies that have led to criticisms of the effective market hypothesis and anomalies are also frequently studied with the purpose of achieving reliable and consistent abnormal returns. Additionally, this is the reason why diverse investing models have been developed based on the factors that explain these anomalies, i.e., the contradictions of the efficient market hypothesis. As a result of the presence of anomalies, the market is not as efficient as once thought (Centineo & Centineo, 2017).

Assuming all investors have the same access to available information, the efficient market hypothesis states that asset prices accurately reflect all information in the market. That is, assets are always correctly valued since the price of an asset reflects its intrinsic value. Several empirical evidence supported these statements of the Efficient Market Hypothesis. In real life, that implies that there is no possibility of earning abnormal returns unless you take more risk when investing (Fama, 1970). The fact that there are factors that outperform the returns expected by the CAPM is something that stands in conflict with the assumptions of the efficient market hypothesis as well as the capital asset model itself (Black et al., 1972). As such, factor investing needs further research, in different markets, time periods and different settings overall. As long as abnormal returns are being made, there will be interest in trying to find new factors to use for higher returns, and with the efficient market hypothesis being quite central in finance literature and theory, testing to what extent the markets are efficient will continue to be interesting.

1.2 Chosen factors

This section will present specifically which factors were chosen for this paper and why. The factors are described in more detail under the theory section.

Part of the Fama-French three-factor model (Fama & French, 1992), the size factor was discovered by Banz (1981), who showed that smaller firms had outperformed larger firms for about 40 years in contrast to the predictions of the capital asset pricing model. This factor was mainly chosen because it is one of the most used in research and as such it was deemed to be a staple factor for this type of research. It was also deemed interesting to see what type of tech/hi-tech companies were most promising for investors, large or small.

The other additional factor (compared to the CAPM) to go along with size in the Fama-French three-factor model is the value factor (Fama & French, 1992). This factor says that investors in general get abnormally high returns from “value” companies rather than growth ones. In other words, stocks that have a high Book-to-Market Ratio outperform those with a lower ratio. This, as with the previous factor was deemed a good add to the analysis due to it being one of the most researched as well as part of the Fama-French three-factor model. In the tech market, where there are high expectations for growth opportunities, the existence of high P/B ratios can be seen as intriguing.

The momentum effect was documented by Jegadeesh and Titman (1993), who observed that companies that have gotten good returns in a previous period are likely to outperform again compared to companies that did poorly. Carhart (1997) proposed a new asset pricing model with four factors by adding the momentum factor to the Fama-French three-factor model; this model is sometimes referred to as the Fama-French four-factor model. Previous research has shown that high tech stocks show higher momentum returns than lower tech equivalents (Shaker Ahmed & Alhadab, 2020). Based on this, the momentum factor was deemed too important to ignore in this paper.

The low-risk or low-volatility factor is based on the empirical observation that high risk stocks do not always give as much of a risk premium as would be predicted by the CAPM. Instead, it was shown that low-volatility stocks had better risk-adjusted returns (Black et al., 1972). High tech stocks have been shown to have higher volatility than the overall market (Gharbi et al., 2014). Research in 2014 has also brought up that this could be due to intense R&D in this sector, creating increased information asymmetry (Gharbi et al., 2014). With these observations in mind, the low-volatility factor sorting by idiosyncratic volatility was chosen as one of the factors to test.

The illiquidity factor was included to include a volume-based factor, which according to previous research does indeed explain some of the excess return not explained by increased risk (Amihud, 2002). This factor suggests that there is expected excess returns to be had from expected illiquidity. In other words, the market compensates for stocks that are harder to trade by charging less for equities with a higher return.

The next factor, adopted by Fama and French into their five-factor model, is the profitability factor (Fama & French, 2015). The profitability factor was added to this paper in order to be consistent and test the newer model proposed by Fama and French (2015). This factor suggests that the stocks of companies that have had a more robust operating profitability for the last 12 months provide better returns than those who had weaker operating profitability.

In the same paper, Fama and French (2015) introduced the investment factor to their model. The factor was introduced to this paper for the same reason as the previous, to continue to investigate the prominent Fama-French models. This factor affirms that the stocks of companies that are conservative in their investments outperform the stocks of companies that make aggressive investments.

1.3 Purpose and research questions

The purpose of this study is to examine whether applying factor investing as a trading strategy on US technology stocks generates higher risk adjusted returns, compared to what the efficient market hypothesis and CAPM predicts. In addition, the authors aim to examine whether applying a range of factors provides higher average returns as well as risk adjusted returns when applied to the tech sector compared to the rest of the market. This results in the following research questions:

I) For what factors does a portfolio of tech stocks utilizing a factor strategy produce abnormal returns?

II) How do those abnormal returns differ from a portfolio of non-tech stocks using the same strategy?

III) What is the difference for risk adjusted returns?

Due to the lack of academic studies within the area of factor investing in tech stocks, the findings of this study provide contributions that may benefit market participants by determining whether the chosen factors generate abnormal returns when applying them to technology stocks. Discussing the performance of factor investing historically, the findings of this study will also contribute practically to the investment field, allowing investors to understand how specific factors may perform in the future. Specifically, it adds more data to the field of factor investing, especially in the tech industry. The results of this study could further improve factor models as well as potentially lead to further research in this area. The paper also builds on the tech stock selection of Kile and Philips (Kile & Phillips, 2009), providing factor research on a sample that has been systematically picked based on previous research.

Factor investing as a strategy was chosen for the study due to its interesting conflicts with the CAPM and the theory that higher returns should only be attainable through taking more risk (Sharpe, 1964). There are a large variety of factors that have been researched so far, such as the classic Fama & French 3 factor model (Fama & French, The Cross-Section of Expected Stock Returns, 1992) but as there are still new factors to be found, and new markets to test them in, research in this relatively young area is still interesting from both an academic and investor perspective.

The high-tech sector was chosen for this paper due to its importance in today's economy as well as the issues making investor decisions difficult in this area, calling for more information or alternative investing strategies. As previously mentioned, there is a correlation between the high-tech sector and growth in advanced economies and investors might have a harder time making investment decisions. This is at least partly due to having to understand new scientific concepts as well as there being less physical collateral due to a lot of value being tied up in research and development for these firms. (Brown, Martinsson, & Petersen, 2017) Along the same line, it has been noted by previous researchers that the higher volatility might come with higher returns (Gharbi, Sahut, & Teulon, 2014) and so this makes investigating the factor effects on this sector even more interesting for investors.

1.4 Limitations

To ensure a good quality for this study and its method, the authors had to make several limitations that might have affected the outcome of this study. However, limitations were necessary due to lack of resources and to draw significant and reliable conclusions of this study.

Initially, the authors have limited the sample selection to technology stocks. The reason for this is the technology industry behaving differently compared to other industries in terms of volatility and capitalization of this sector as previously mentioned, as well as the increased popularity. Although the technology sector is enormous, the academic research covering factor investing is insufficient. Academic evidence shows that factors such as value, momentum, small capitalization, and low volatility stocks systematically outperforms a portfolio consisting of risk-free assets and the world stock market index but there is lack of research regarding applying these factors on the technology industries, which is why the authors chose to limit this study to the technology stocks. The result of this study could be useful for market participants since it adds academic evidence to this area. It contributes to adding more data to this field, specifically to factor investing within the tech industry.

The selection of companies to include in the following study was based on the research of Kile and Philips (2009). The focus is on the US tech sector as it hosts some of the largest names in the tech world today, but also to a large extent due to the availability of comparable data. Kile and Philips (2009) suggested SIC-codes that identify companies in the high-tech industry. This resulted in 2927 stocks considered high-tech stocks. The time for the testing was limited to the years for which data was available in the WRDS database. Due to this, the period investigated in this paper was from 1980 until the end of 2021.

Another limitation that impacted on the study is the leaving out of transaction costs. Mainly at the times of rebalancing, the trading of stocks would incur transaction costs with the broker used as they most often demand a fee for their services. This was deemed appropriate due to a few key points, partly due to comparability, where achieving a reasonable transaction cost relevant across brokers as well as over geographic differences was not deemed to be worth it. This is especially due to one of the key assumptions in the competing theory (meaning the capital asset pricing model), being the exclusion of transaction costs. It should be stated however, that due to these costs being excluded, the total returns produced by the models in this paper will be higher than would be the case in a real-life scenario.

2. Theory and previous research

This section will introduce the reader to the theoretical framework behind this paper and previous research related to the area of the study.

2.1 Theoretical framework

2.1.1 Efficient market hypothesis

The efficiency of a market is defined by the fact that its prices always reflect all the available information. A market that is efficient occurs when market participants actively compete to maximize profits. They continuously try to predict market values with the tools available to them. As a result, securities will eventually be priced at any time reflecting all the information available to the market including current as well as expected information. As such, the current price of a security can be seen as a good indicator of its intrinsic value. Thus, stocks can neither be undervalued nor overvalued because they are traded at their fair value (Fama, 1970).

Fama (1970) presents the following three conditions for a market that is efficient and where the price in such a market always reflects the available information:

1. Trading securities does not incur transaction costs.
2. Participants must have access to all available information without charge
3. Each party agrees that current information will affect the current security prices and distributions of future prices for each security.

Three different versions of the efficient market hypothesis exist, and all three versions are of varying degrees of the hypothesis: weak, semi-strong, and strong (Fama, 1970).

The weak version of the efficient market hypothesis claims that current asset prices reflect all information contained in historical prices. This implies that using investment strategies based on historical prices will not generate excess returns (Jain, 2012).

The idea behind semi-strong-form efficiency is that prices reflect all publicly available information and that they are updated instantly to reflect new information. Share prices adjust rapidly to publicly available new information, and they do so unbiasedly, such that trading on that information cannot produce excess returns (Jain, 2012).

The strong version of the efficient market hypothesis claims that all asset prices reflect all public as well as private information. Hidden and insider information are also fully reflected in the stock prices. This implies that no information in the market can give investors an advantage generating excess return (Jain, 2012).

Since the introduction of the Efficient market hypothesis, this model has received considerable attention. Empirical evidence shows that there are inconsistencies in the model described as anomalies. These anomalies can result in characteristics that lead to higher returns than predicted by the efficient market hypothesis. Thus, it is proven that the efficient market hypothesis doesn’t always hold (Jain, 2012).

Relating the efficient market hypothesis to this paper specifically, the weak form of the theory says that using historical prices as a basis for an investment strategy does not generate abnormal returns. This is exactly what the momentum factor aims to do however, and if found to be significant will violate this version of the theory. For the other factors, it would be the semi-strong version of the efficient market hypothesis that would be violated if they prove to generate abnormal returns, as they are based on publicly traded information.

2.1.2 Capital asset pricing model

The CAPM is a model mainly derived from Black (1972), Lintner (1965), Sharpe (1964) and Treynor (1961). The model is commonly used in finance to price risky securities, estimate expected returns on assets depending on assets’ risk and costs as well as estimating the cost of capital for firms etc.
The model explains the relationship between the risk of investing in an asset and the expected return for assets. As illustrated in figure 2., model states that under certain assumptions the expected return on an asset is equivalent to a risk premium and a risk-free return, where the risk premium is based on the beta of an asset.

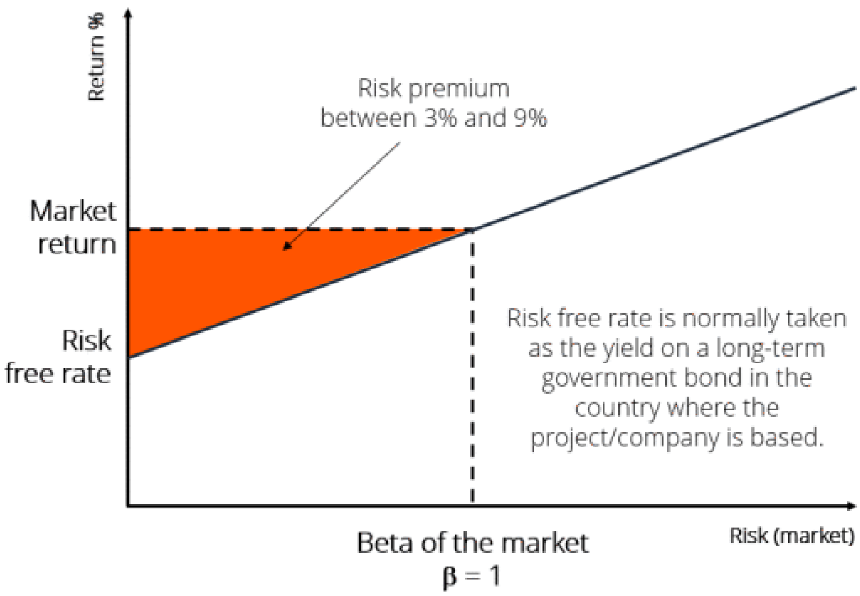

Figure 2. Graph illustrating the concept of CAPM.

Figure 2 shows the relationship between return and systematic or market risk fundamental to the CAPM. On the Y axis the return in percentage is presented, and on the X axis the risk taken related to the market or systematic risk is shown. Along the line, the Beta (risk relative to the market) increases with return, and a line is drawn from the Beta line to the level of return that level of beta brings with it. The distance between this line and the risk-free rate of return is then the risk premium at the taken level of beta. This illustrates the CAPM assertion that any return above the risk free comes with a higher Beta or risk relative to the market, and that this higher return is a premium for accepted risk.

CAPM is based on the following assumptions. (1) Investors share the same opinions regarding the possibilities of all assets reaching different end-of-market values. In terms of returns on existing assets, they have a common joint probability distribution. (2) The expected return on the available assets is jointly normally distributed. (3) Portfolios are constructed by investors to maximize their end-of-period utility of wealth and risk aversion is common among investors. (4) In addition to having the opportunity to borrow or lend any amount at the risk-free interest rate, investors can have a long or short position regardless of size and asset. (Black, 1972)

Regarding measuring risk and predicting how expected return and risk are related, the CAPM provides powerful and pleasing predictions. Although empirical evidence of the CAPM is weak and insufficient, making the model invalid when applied in real life. Essentially, the

CAPM's empirical problems are likely due to theoretical flaws, resulting from simplifying assumptions, as well as complications in implementing valid tests of the model. (Fama & French, 2004)

Since all information is already incorporated in the price of securities, abnormal returns cannot be earned by searching for mispriced securities, according to The Efficient Market Hypothesis. Some market patterns and strategies do appear, however, to be able to generate abnormal returns, thus violating the efficient market hypothesis. In fact, some studies state that actors or strategies outperforming the market reflect higher risk and should generate higher returns as a result.

Furthermore, an investment's expected return can be determined based on systematic risk using the Capital Asset Pricing Model. Factor investing is considered to be an extension of the Capital Asset Pricing Model. Factor investing considers multiple risk factors that are expected to affect returns on assets, rather than a single systematic risk factor (beta) as in CAPM. In conclusion, markets may not always be fully efficient, and anomalies do exist, which could lead to abnormal returns. By incorporating factor investing, the authors aim to study how growth and returns are explained by more than just beta alone, such as in CAPM.

2.1.3 Fama French factor models

Fama French 3-factor model

The Fama and French three factor model is an expansion of the capital asset pricing model, developed by Fama and French in 1992. It combines a market risk factor, a size risk factor, and a value risk factor into the CAPM. The model aims to describe stock return through these three factors. Adding additional factors to the CAPM did in fact improve its ability to predict the excess return of portfolios. According to Fama and French (1995) there is a covariance between a company's size and book-to-market ratio, why the additional variables expressing the covariance were added to the CAPM. The size factor and the book-to-market factor generates the Fama-French Three-factor model.

Fama French 4-factor model

The Fama French 4-factor model is very similar to the 3-factor one, with the momentum factor added to the model. One of the earlier observations of this was made in 1993 by Jagadeesh and Titman when they were researching buying previous winners and selling previous losers over different holding periods (Jegadeesh & Titman, 1993).

The Carhart four-factor model is based on the work of Fama and French's three factor model. It was developed by Carhart (1997) for the purpose of valuing mutual funds. Besides the three factors Fama and French identified, Carhart (1997) adds a fourth: Momentum. Momentum refers to an asset's tendency to continue on a certain trend, rising or falling. The addition of the fourth factor, according to Carhart (1997), led to more accurate portfolio return measurements.

Fama & French 5 factor model

Evidence show that the Fama-French three-factor model is insufficient for predicting expected returns due to it overlooking variations in average returns with respect to investment and profitability. (Fama & French, 2015) Furthermore, studies show that profitable firms generate significantly higher returns compared to unprofitable firms, even though they tend to have higher market capitalization and a lower book-to-market ratio. Novy-Marx (2013). Also, it has been shown that firms that increase capital expenditures substantially achieve less positive adjusted returns, according to (Fama & French, 2015). As a result of the findings above, the Fama-French five-factor model (2015) includes following two additional variables that account for the effect of investments and profitability.

2.2 Other previous factor research

As cross-sectional asset pricing literature and research has been conducted, critique has been aimed at the validity of some of these predictions. In response to this, Chen and Zimmermann started a project testing previously studied factors via openly available data as well as open-source code (Chen & Zimmermann, 2022). In contrast to some previous research, this work replicated the process of the original research when evaluating the different predictors.

This reproduction seems to have been successful, especially when comparing it to previous attempts at reproduction and predictability, redeeming some of the previous research as well as providing increased replicability through their open-source code as well as predictors that can be easily used together with readily available data from known databases. Chen & Zimmermann’s paper has been significantly important to this research, outlining the construction of predictors as well as providing data on them.

2.2.1 Previous factor research on tech

In their paper “*Momentum, asymmetric volatility and idiosyncratic risk-momentum relation: Does technology-sector matter?”* ((Shaker Ahmed & Alhadab, 2020) Ahmed and Alhadab made a comparison between high- and low-tech firms when it comes to factors such as momentum returns, volatility and idiosyncratic risk relative to momentum returns. Their research showed stronger momentum returns for high-tech firms when compared to lower-tech firms. According to them, these momentum returns were not significantly correlated to idiosyncratic risk for high tech firms and for low tech, momentum returns were negatively correlated with idiosyncratic risk (Shaker Ahmed & Alhadab, 2020).

Economic innovation and growth are largely driven by high-technology industries, according to Ahmad & Aldahab (2020). Essentially investing in R&D activities leads to innovation and competitive advantage in the high-technology sector, i.e., enabling corporates within the technology industry to innovate and gain a competitive advantage that will lead to long-term economic growth. At least 50 % of the United States GDP and 80 % of its R&D activities are accounted for by the high technology sector, thus making it a major driver in the economy. (Ahmad & Aldahab, 2020)

Ahmad & Aldahab (2020) consider the technology sector as behaving differently than other sectors for three main reasons. To begin with, high technology firms are more likely to engage in R&D activities as well as having higher unreported asset levels. Secondly, high-tech firms’ predictable earnings and returns are primarily driven by intangible assets, while R&D investments generate greater uncertainty. Thirdly, as mentioned, high-tech firms exhibit a high proportion of intangible assets compared to other sectors. About 50 % of the R&D expenditures go to scientists, engineers and those who are creating the intangible assets. The firm might lose these intangible assets to other firms if those who created them decide to leave. As a consequence of this, high-tech firms underinvest at a greater rate, obtain fewer finances externally that are aimed for R&D activities, and they also face higher levels of risk (Ahmad & Aldahab, 2020).

Zingales (2000) discusses different corporate finance theories and outlines the characteristics of different types of firms. According to him, high-tech firms have unique characteristics. They are knowledge-based organizations and due to them being non-vertically integrated as well as having a high human capital intensity, they challenge traditional firm theory. Furthermore, Zingales (2000) argues for high-tech firms have a competitive advantage compared to traditional firms. It is unique that high-tech firms have an intensive amount of intangible assets such as patents, brands, talented human capital and great investments in R&D.

In line with this, Aboody and Lev (2000) have concluded that high-tech firms are found to exhibit unique organizational structures and activities, as well as distinctive sources of competitive advantage, thus supporting the view of comprehensive differences between high-tech and low-tech firms. Furthermore, Aboody and Lev (2000) have concluded that insiders in high-tech firms outperform insiders in low-tech firms, making investments in high-tech firms more profitable. Also, since high-tech firms invest in R&D activities to a greater extent, they pay lower or no dividends at all, compared to other firms. There is evidence showing that firms that don’t pay dividends experience higher momentum profits. This is in line with the study of 5795 US high-tech and low-tech firms, where Ahmad & Aldahab (2020) concluded that high-tech firms always outperform low-tech firms based on momentum profits. Additionally, the degree of consensus among analysts decreases when R&D expenditures and the associated asymmetric information are substantial, as proved by Barron et al. (2002). Therefore, the level of analyst consensus for high-tech firms is expected to be lower than that of low-tech firms (Barron et al., 2002).

Borah et al., (2018) have examined the relationship between diversification and firm value and found that the degree of value reduction depends on a firm's level of technology intensity. Furthermore, the study shows that there are significant differences in value declines between high-tech and low-tech firms due to asymmetric information issues in technology-intensive industries. Firms with higher intangible asset ratios and greater R&D investments experience even greater negative valuation effects (Borah et al., 2018).

2.3 Selection and segmentation of tech stock

When it comes to what stocks to include in the “Tech” or “High-tech” classification, there can surely be debates about which should be included in a good sample of firms, and it is of high importance in defining what is a high-tech industry and what is not. Depending on the sample, the results of any analytical work will vary, which is why it is important that the sample is chosen in a reasonable way to avoid blatant errors.

A classic way to achieve this is to use SIC-classification. Standardized Industry Classification codes are often used by empirical research in finance, business and similar fields to segment firms, according to Kile and Phillips (Kile & Phillips, 2009) This methodology had been criticized however according to their paper, why they went ahead with a paper trying to reduce sampling error in stock selection by analyzing business characteristics and double checking selection with other classification systems, such as the NAICS and GICS code systems.

In finance, economics, and accounting research the SIC is widely used and is in fact the dominant system. Prior research underlines its superiority when targeting high-tech in forecast analyses (Kile & Philips, 2009). However, since the SIC was assigned by the American government in the 1930s as a system to categorize the economy into 11 major divisions and since it’s no longer being revised, studies have shown its lack of reflecting emerging high-tech industries. In addition, using the SIC system when dealing with conglomerate firms may lead to heterogeneous grouping in terms of financial characteristics (Kile & Philips, 2009) Nevertheless, using SIC is more beneficial for comparability purposes since there are a great number of studies using this classification (Kile & Philips, 2009). In addition, for maximum data availability and simplicity of attaining data as well as for the substantial amount of evidence proving the superiority of this classification, the optimal SIC definition provided by Kile & Philips (2009) will be used.

2.3.1 Factor selection

Factors are considered as characteristics that could explain the risk and return of securities. Factors can’t be observed directly and there is no straightforward method for how to define or estimate factors. Finding factors with a strong power of explanation over wide raging firms as well as factors being consistent over time are generally of greatest interest for researchers (Bender et al., 2013).

Factors can be classified in mainly three categories: fundamental, statistical, and macroeconomic. Fundamental factors are the most used today. Fundamental factors include characteristics of a firm such as valuation ratios, country membership, etc. Identifying statistical factors could be done using techniques such as principal components analysis (PCA). Macroeconomic factors refer to a wide range of measures such as GDP, GNP and inflation (Bender et al., 2013). Value, momentum, dividend yield, quality and low size are the most well-known factors used in academic research. In fact, mentioned factors have generated excess returns above the market, according to empirical studies (Bender et al., 2013).

2.3.2 Factors

Size

The size factor can largely be attributed to the 1981 paper *The relationship between return and market value of common stocks,* where Rolf W Banz shows that for at least the 40 previous years, smaller firms had outperformed large firms in a way that would suggest the CAPM model to be wrong (Banz, 1981). The outperformance that smaller firms could generate has been observed in both developed and emerging markets across the world. The small cap premium is consistent even after controlling for variables such as leverage, the market beta, momentum etc. (Bender et al., 2013).

Why a small cap premium exists could be explained by numerous theories. For instance, Fama and French (1992) find a strong relation between size and return which can be explained by the fact that small caps generally have higher systematic risk. Therefore, this higher systematic risk tends to generate a higher return premium (Fama & French, 1992).

Banz (1981) does however, leave it open that it might not be size, but an unknown factor that size acts as a proxy for that causes this abnormality. This factor has later been reaffirmed in research, one example of such being in 2017 when Houweling and Van Zundert confirmed a higher Sharpe ratio for the size factor when looking at corporate bonds. (Houweling & Van Zundert, 2017). As noted above, this factor is also one of the commonly included factors in research. Hence, it was included in the analysis of this paper, especially as the factor might be explained by an unknown related factor. As noted above, this factor is also one of the commonly included factors in research. Hence, it was included in the analysis of this paper, especially as the factor might be explained by an unknown related factor.

Value

One of the factors included in the famous Fama-French 3 model, along with the CAPM and the previously mentioned Size factor, is the Value factor. Fama and French (Fama & French, 1992) attribute the discovery of this factor to Stattman (Stattman, 1980) as well as Rosenberg, Reid and Lanstein (Rosenberg, Reid, & Lanstein, 1985) The way to measure this factor has varied between papers, but since Fama-French is a highly referenced work and household name, this paper uses their definition of value, Book-to-price. In other words, this factor is measured by the relation between the book value of equity compared to the market value or price.

Momentum

One of the factors used in the building of the factor portfolios is the momentum factor. Momentum factor refers to exposure to stocks that have shown the highest risk adjusted returns in the past six to twelve months. Momentum capturing past performance implies one could take advantage of the fact that stock prices tend to show the same trend over certain horizons. In other words, that means stocks with a rising trend continue to rise and stocks with a falling trend continue to fall. Empirical studies on the US stock market as well as on the European market show that Momentum investing, i.e., buying past winners and selling past losers generated positive abnormal returns (Bender et al., 2013).

In their 2020 paper *Momentum, asymmetric volatility and idiosyncratic risk-momentum relation: Does technology-sector matter?* (Shaker Ahmed & Alhadab, 2020) the researchers conclude through their constructed portfolios of high vs low tech firms that high-tech firms do in fact generate higher abnormal momentum returns than their lower tech counterparts, which is why this paper has used momentum as one of the factors when constructing the portfolio to contribute to the portfolio returns.

Low risk

Classical financial researchers Black and Scholes along with Jensen determined in 1972 that the returns of stocks were not perfectly proportional to their betas (Black et al., 1972), and

thus the low-risk or low-volatility factor was born, where lower risk shares do not necessarily earn less returns due to missing the risk-premium as suggested by the CAPM. In other words, it suggests that lower risk equities might earn superior risk-adjusted returns.
Less risky assets outperforming the market conflicts with one of the most basic principles in finance, namely that more risky assets tend to generate higher return in the form of a risk premium.

High-tech stocks tend to show an increased level of volatility (Gharbi et al., 2014) and in 2014 Gharbi, Sahut and Teulon proposed that this might be due to intense R&D causing information asymmetry about the profitability of the firm, which in turn makes investors less sure and the stock more volatile. With this in mind, the low-volatility or low-risk factor was thought to be important in the analysis of this paper.

Illiquidity

The ease with which an asset can be traded in the market at a price based on its intrinsic value is referred to as liquidity. That is the ease with which transactions may be executed without excessive costs and complexity. Ceteris paribus, it's harder and more expensive to trade a less liquid stock. Due to this characteristic, illiquid stocks are less attractive than those with more liquidity and therefore they are expected that illiquid stocks will command a premium to be held, which is confirmed by some academic studies.

Amihud and Mendelson (1986) have documented patterns in stock return that could be related to liquidity. According to Amihud and Mendelson (1986), a liquidity factor emerges naturally in the presence of friction. Although they assume frictions don't exist among the most influential asset pricing models. For instance, the capital asset pricing model states that there is a linear relationship between market beta and expected stock return. But there is evidence that the CAPM does not hold in real life. Thus, making it possible to take advantage of this when investing. According to Amihud and Mendelson, expected returns can partially be explained by considering the liquidity factor. They conclude that differences in stock liquidity contribute to differences in expected stock returns.

Profitability

A company´s profitability measures its ability to generate profits over time and it is a crucial factor in assessing the overall financial health of a company. Since it represents the amount of profit a company produces relative to its revenue or investment, it is considered a key factor when measuring the success of a company.

Businesses measures profitability in several ways, including net profit margin, gross profit margin, return on equity (ROE) and return on investment (ROI). A company´s Return on equity is frequently used by investors to assess the profitability of a company as well as comparing it to other investments. ROE indicates how much profit a company generates relative to its shareholders' investments. According to Hou, Xue and Zhang, return on equity (ROE) is income before extraordinary items, divided by 1-quarter-lagged book equity (Hou, Xue, & Zhang, 2017).

Evidence shows that profitability is a significant factor when assessing the performance of a company. For instance, Okur and Kaya (2021) have studied the relationship between profitability and firm value in the Turkish industry, concluding that the value of a firm is significantly influenced by profitability. Also, Gupta and Sharma (2019) have studied profitability´s impact on firms in the pharmaceutical industry in India, finding that profitability contributed significantly to a company´s performance.

The profitability factor ultimately used in this paper is the same one used by Fama & French, namely operating profitability (Fama & French, A Five-Factor Asset Pricing Model, 2014). This factor was introduced in 2012 as a good controlling variable in models with earnings anomalies (Novy-Marx, 2013) and is defined as the gross revenues reduced by cost of goods sold in relation to its assets.

Investment

A company´s asset growth factor represents the rate at which its assets are growing over time. This is widely used in assessing an organization's long-term growth potential and predicting its future earnings.

The investment factor captures the negative relationship between future profitability and a company´s investment in assets, why it is an important determinant of stock returns. Stocks of companies that invest more tend to display lower average returns than stocks that invest less, which is known as the asset growth anomaly. (Cooper, Gulen, & Schill, 2008) Many studies have found that the investment factor is a significant determinant of stock returns. For instance, the investment factor was identified as one of the most robust and significant factors explaining stock returns across markets and asset classes, according to. (Azness., et al. 2014) Many studies have found that the investment factor is a significant determinant of stock returns. For instance, the investment factor was identified as one of the most robust and significant factors explaining stock returns across markets and asset classes, according to (Azness., et al. 2014)

The asset growth factor used in this paper is the one mentioned above, namely the one introduced by Cooper, Gulen and Schill and used previously in the "Replicating anomalies" work of Hou, Xue and Zhang (Hou, Xue, & Zhang, 2017).

3. Methodology

3.1 Data sources

Monthly returns on individual US common stocks were obtained from the Center for Research in Security Prices (CRSP) database and were downloaded via the Wharton Research Data Services (WRDS). Monthly data on the stocks' market equity (price times the number of stocks outstanding) was obtained from the same source. Market equity data was used when creating value-weighted portfolios, as well as to create portfolios sorted on firm size. Return data, price and market equity was gathered from the end of 1979 until December of 2021, to get as large a data sample as possible to test on.

Monthly data on individual stock characteristics (other than size) were downloaded from OpenAssetPricing.com where Chen and Zimmermann provide data used in their 2022 paper for open-source use (Chen & Zimmermann, 2022)

This paper relies on the previous work of Kile and Philips (2009) and uses SIC-codes to classify individual stocks as either "tech" or "non-tech" stocks*. Companies' SIC-codes were also obtained via WRDS. This resulted in a total of 5867 unique tech companies as well as 18333 unique non-tech companies over the time period targeted.

3.2 Weighing strategies

There are 2 main strategies for choosing how much of each included stock should be "bought" in a portfolio, namely equal-weighted or value-weighted.

An equal weighted portfolio has an equal amount of its resources invested in each stock. In contrast to this, the value-weighted portfolio puts different "weight" into different stocks based on a property or value of the stock. A frequently used value for such a weighing is market equity or market capitalization. When a portfolio is weighed in this manner, the portfolio makes a larger investment into stocks of larger companies according to their size.

*SIC Codes for tech sample: 283, 357, 366, 367, 382, 384, 481, 482, 489, 737, 873

To keep consistency throughout the testing of the different factors, it was decided that one of these should be used for all factors, and with an equal-weighted strategy being the most commonly used in the original papers of the factors included in this paper, this was deemed to be most relevant. The results of the factors using a value-weighted strategy are also included as a subsection after the main results for robustness and comparison purposes under the heading “Alternative results”.

3.3 Portfolio formation

3.3.1 Portfolio sorting

When creating the portfolios used in this paper, stocks were sorted according to one stock characteristic at a time. The portfolio sorting was done either every month or once every year (at the end of June) depending on the data used in the factor (accounting or live market data) or simply the design of the original paper.

Once the sorting according to the specific factor was done, the stocks were put into three different portfolios according to their ranking in said factor, the 30% lowest ranking was one portfolio, the 40% middle ranking was one and finally the top 30% ranked in the factor were put into a final portfolio. The average monthly returns of these portfolios are introduced in the results section and are available in full in the appendix. These portfolios were then used to create the long-short portfolios introduced in the next subsection.

Factor	Acronym	Sign	Rebalanced
Size	Size	-	Yearly
Value	Bmdec	+	Yearly
Momentum	Mom12m	+	Monthly
Idiosyncratic Risk	IdioRisk	-	Monthly
Illiquidity	Illiquidity	+	Yearly
Profitability	OperProf	+	Yearly
Investment	AssetGrowth	-	Yearly

Table 1, Showing some details about the nature of factors used.

Table 1 above shows the name of the factor used in this paper as well as the acronym or technical name used by Chen and Zimmermann in their data set (Chen & Zimmermann, 2022). It also gives an indication of whether an increase in the factor is predicted to produce positive or negative abnormal returns, or in other words whether the factor portfolio is of a low minus high or high minus low nature. Finally, one can also read in this table how often the long-short portfolio of this factor is rebalanced in the actual testing part of the paper.

3.3.2 Long-short portfolios

In order to test the returns of the factors on the tech and non-tech samples, so called long-short portfolios were constructed. Different factors have different suggested ways to construct these in the papers that originally introduced them, however for the sake of consistency the long-short portfolios were constructed in the same way for each factor.

The breakpoints chosen are the same as described by Fama & French for the HML; CMA and RMW portfolios (Fama & French, 2015) namely the 30th and 70th percentile. In other words, the percentile portfolios are divided into three groups, the 30% bottom, 40% in the middle and the 30% top sorted by the factor variable.

The long-short portfolios were then created by subtracting the returns of one 30% group from the other, either the top group minus the bottom or the other way around, based on the nature of the factor. This was done for each factor, one for the tech sample and for the non-tech sample.

The size portfolio is created by ranking by the total market cap and taking the smallest minus the biggest, which in Table 1 is indicated by the minus sign of the factor, in contrast to some of the other factors where a plus sign indicates a portfolio is created by taking high minus low instead. The value one is instead ranked by B/M or Book-to-market ratio and is created by taking the high minus the low. The momentum portfolio is ranked by the stock returns of the previous 12 months, lagged by 1 month. After this, the winners are reduced by the losers to create the portfolio. This portfolio is also updated each month in contrast to the rest that are updated each 12 months. The idiosyncratic risk portfolio is created by ranking the idiosyncratic risk and taking the lowest risk stocks minus the highest. The illiquidity portfolio is ranked by illiquidity, then the portfolios are created by taking the most illiquid minus the least. Next, the profitability is ranked by operating profitability and the most robust is reduced by the weakest. Finally, the investment one is created by ranking asset growth and taking the conservative minus the aggressive.

3.4 Measures of portfolio performance

This section aims to explain the origin of the presented results and how these were calculated to the reader. First for the long-short portfolios presented in the first main results table, followed by an explanation of the results shown in the second difference table.

3.4.1 Performance of the long-short portfolios

Once the long-short portfolios are formed, the first metric that is interesting for this paper is the average monthly returns, both by itself and for further testing. This is as it sounds the returns the long-short portfolio in question made on average in a month during the testing period, and is calculated using the formula:

$$\bar{R}_f^j = \frac{1}{M}\sum_{t=1}^{M} R_{f,t}^j \tag{1}$$

Where the returns $R_{f,t}^j$, include the notations *f* for the specific factor, *j* for tech or non-tech as well as *t* to denote the specific month. For example, $R_{Size,2}^{Tech}$ would indicate the returns made during the second month by the Size-factor long-short portfolio made up of tech stocks. These returns are commonly also called factor returns. In order to check whether these returns were significant and not a fluke, a t-test was carried out on each long-short portfolio with the null hypothesis:

$$H_0: \bar{R}_f^j = 0 \tag{2}$$

This is the null given that the efficient market hypothesis would indicate that there should be no significant difference in returns between stocks with a higher or lower level of specific factors and statistically significant returns violate this. In the corresponding table in the results section, the result of this test is reported in p-value form. Another parameter of interest is the alpha, calculated using the regression:

$$R_{f,t}^j = \alpha_f^j + \beta_f^j * R_{Mkt,t}^e + \varepsilon_t \tag{3}$$

Where the beta, which is the coefficient that indicates how the returns are correlated with the excess returns of the market, is denoted by β_f^j where the *f* again stands for the specific factor used, and the *j* whether it is concerning the tech or non-tech sample. The excess market return is denoted by $R_{Mkt,t}^e$ where the *t* indicates the specific month of interest, and the ε_t of course denotes the error term or residuals in the same month. The alpha is denoted by α_f^j and can be thought of as the abnormal returns not predicted by the taken market risk in the CAPM model (Jensen, 1967). Therefore, it is interesting in the context of this paper, as a statistically significant alpha indicates returns that are not predicted by the portfolio returns correlation with the market, or in other words with systematic risk. Once the alpha had been established, a t-test is run for this measurement as well in order to see if statistically significant, the null being once again:

$$H_0 : \alpha_f^j = 0 \tag{4}$$

Due to the assumption that markets are efficient, and that any abnormal returns should not be made in the CAPM model that are not linked to systematic risk, hence any statistically significant deviation from this is interesting. The result of this test is presented as a P-value once again. Next, the riskiness of the portfolios was measured, in practice called the monthly volatility and often in statistics the standard deviation. This was done using a computer of course but along the lines of the formula:

$$\sqrt{\frac{\sum_{t=1}^{T}(R_{f,t}^j - \bar{R}_f^j)}{n-1}} = SD\left(R_{f,t}^j\right) \tag{5}$$

The final measurement introduced in the main results table is the Sharpe Ratio. This is a measurement of risk-adjusted return, where the average return is divided by the volatility or standard deviation:

$$SR_f^j = \frac{\bar{R}_f^j}{SD\left(R_{f,t}^j\right)} \tag{6}$$

By using this measure, investors can compare portfolios with different return and risk profiles with each other to find the better investment, for example, even though one portfolio provides higher average returns than another one, it may be too risky to justify it compared to a safer portfolio with significantly lower risk.

3.4.2 Difference in performance between tech and non-tech stocks

In order to investigate the significance of any differences between factor returns between the tech and non-tech samples, what will be called difference portfolios were created. One was created for each factor included in this paper. In particular, for a specific factor *f* in month *t*, let:

$$R_{f,t}^{diff} = R_{f,t}^{Tech} - R_{f,t}^{NonTech} \tag{7}$$

That is, $R_{f,t}^{diff}$ is the difference between the return of factor *f* created from tech stocks and the return on the same factor when created from non-tech stocks. If the return difference is positive, the factor has a higher return when it is formed from tech stocks. If, on the other hand, $R_{f,t}^{diff}$ is negative, the factor has a higher return when it is created from non-tech stocks.

The first measurement presented of the difference portfolio is the average monthly return, calculated by the formula:

$$\bar{R}_{f}^{diff} = \frac{1}{M}\sum_{t=1}^{M} R_{f,t}^{diff} \tag{8}$$

This is simply the average return generated by the difference portfolios during a month. In addition to this, another t-test is performed to check the significance of the returns of these difference portfolios:

$$H_0: \bar{R}_{f}^{diff} = 0 \tag{9}$$

Meaning that the null hypothesis is that there is no difference in returns for the factor in question between tech and non-tech. Then the alpha is presented for the difference portfolios, representing the abnormal returns not predicted by the beta or systemic risk in the CAPM model:

$$R_{f,t}^{diff} = \alpha_{f}^{diff} + \beta_{f}^{diff} * R_{Mkt,t}^{e} + \varepsilon_t \tag{10}$$

Along with this comes another t-test for significance:

$$H_0: \alpha_{f}^{diff} = 0 \tag{11}$$

Which implies that the abnormal returns of the tech sample portfolio are the same as those of the non-tech sample portfolio, in other words:

$$H_0: \alpha_f^{Tech} = \alpha_f^{NonTech} \tag{12}$$

Once again, the result of this t-test is posted in the difference table in the form of a p-value. Finally, it was deemed interesting to compare Sharpe ratios of tech and non-tech, partly in order to establish if one was statistically superior to the other in return versus risk. Formally, the difference would be:

$$SR_f^{diff} = SR_f^{Tech} - SR_f^{NonTech} \tag{13}$$

To see if the Sharpe ratios were significantly different from each other, a HAC inference test was used. This was done using the pre-whitened QS kernel. This was chosen as a method due to it being suggested by Ledoit & Wolf (Ledoit & Wolf, 2008). To check whether there is a significant difference, the null hypothesis can be formalized as follows:

$$H_0: SR_f^{diff} = 0 \tag{14}$$

The result of this test was presented in the form of a p-value in the “difference table”.

3.5 Critical methodology discussion

Validity and reliability are tools used to analyze a scientific study and whether it is done properly. Validity is used to avoid systematic measurement errors, meaning it is used as an accuracy of a measure and to discuss whether the results represent what was intended to be studied. Furthermore, it helps to decide whether the findings of the study are generalizable to other situations. There are two aspects of validity: external and internal.

The degree to which the conclusions of a research study are generalizable to other people, situations and times are considered as external validity. A study's external validity assesses whether the findings are consistent with the reality. (O’Brian & Orn, 2018)

The internal validity of a study is determined by how much a particular manipulation is responsible for the observed effects. In other words, it is a way of determining whether the theory corresponds to what is measured. (O’Brian & Orn, 2018)

In terms of internal validity, the method of this study follows that of previous studies. Thus, the internal validity is at standard level. To examine the purpose of this study, average stock returns have been used in the analysis. Monthly returns are calculated using end-of-month closing prices. In real life, it might not be possible to trade on those prices. Also, transaction costs aren’t considered in this paper, which might have a considerable effect on the validity of this study.

A research method or tool's reliability can be measured by the degree to which it produces consistent results across tests. In other words, if the method is reliable, the results will be the same regardless of the circumstance. In addition, this tool discusses the accuracy and absence of random errors in measurements. (O’Brian & Orn, 2018) This study is based on theories recognized and well established in academia, with prominent scientists such as Fama (1970). Also, for confirmation reasons, data used in this study have been checked with diverse sources. Therefore, even though this study is based on secondary data, the reliability of this study is good.

4. Results

4.1 Initial example

This section is an introduction to how the results in the main results are calculated.

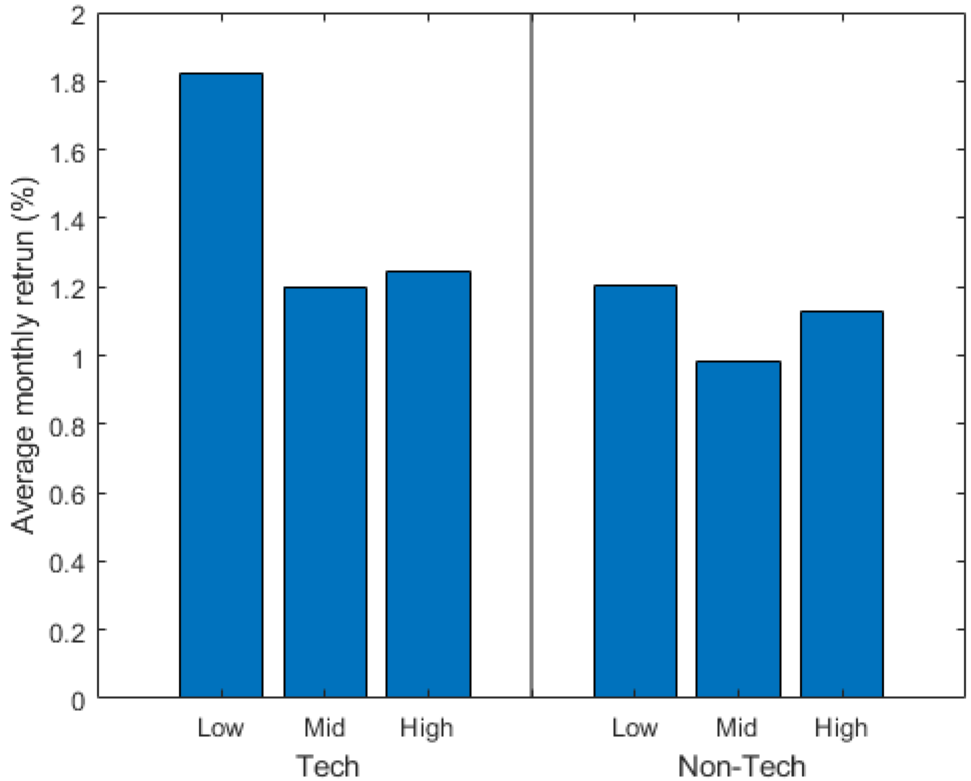

Figure 2: Bar graphs showing the average monthly returns of the highest 30%, mid 40% and lowest 30% sorted by a given factor. In this example, size.

The above graph shows the average monthly returns of the different portfolios created by sorting by the size factor, to the left in tech and to the right in non-tech. By taking the smallest 30% minus the largest 30% or Low – High, the average monthly returns of the Tech and Non-tech sample long-short portfolios for the Size factor was calculated, which is what is presented in the first column of the main results table. This is interesting in order to see if there is a significant difference between the extremes. If one looks at the low and high columns in the "tech" half of Figure 2 above one can observe roughly that the difference between these are the returns presented as 0.58% in the following main results table under size tech, being considered a significant difference. In contrast, if one instead looks at the "non-Tech" columns above, the difference can be observed to be lower, and in the main results table size non-tech returns are considered non-significant. Similar graphs for the other factors can be found in the appendix.

4.2 – Main results Table

The table in this section summarizes the relevant results from the portfolio sorting process described in the previous section. This is followed by analysis for each factor.

Factor EW	$\bar{R}_f^j$ (in %)	$H_0: \bar{R}_f^j = 0$ (p-value)	α_f^j $(in\ \%)$	$H_0: \alpha_f^j = 0$ (p-value)	$SD\left(R_{f,t}^j\right)$ (in %)	SR_f^j
Size Tech	0.58**	0.038	0.71**	0.011	6.18	0.32
Size Non-tech	0.08	0.683	0.22	0.250	4.21	0.06
BM Tech	0.92***	<0.001	1.10***	<0.001	3.25	0.98
BM Non-Tech	0.59***	<0.001	0.73***	<0.001	2.44	0.84
Mom Tech	0.33	0.241	0.46	0.105	6.34	0.18
Mom Non-tech	0.82***	<0.001	0.99***	<0.001	4.52	0.63
Idio Tech	0.24	0.411	0.56**	0.044	6.43	0.13
Idio Non-tech	0.58**	0.013	0.94***	<0.001	5.20	0.39
Illiq Tech	0.61**	0.016	0.76***	0.003	5.60	0.38
Illiq Non-Tech	0.28	0.100	0.48***	0.004	3.85	0.26
Profit Tech	0.46**	0.016	0.68***	<0.001	4.23	0.38
Profit Non-Tech	0.49***	<0.001	0.57***	<0.001	2.40	0.71
Investment Tech	1.03***	<0.001	1.10***	<0.001	3.79	0.94
Investment Non-Tech	0.50***	<0.001	0.54***	<0.001	2.00	0.86

*Table 2. Tech and non-tech results for the long-short portfolio of each factor including return, alpha, standard deviation and Sharpe ratio. *Indicates significance at the 10% level ** Indicates significance at 5% level *** Indicates significance at 1% level.*

The first column in the table above represents the % monthly return produced by the long-short portfolio for each factor, and the second represents how statistically significant that result is. This is then followed by the third column presenting the alpha or abnormal returns compared to the prediction of the CAPM, and the significance of this is presented in column four. The fifth column of the table presents the volatility of the returns produced by the long-short portfolios, expressed in percentage terms. Finally, the last column shows the Sharpe ratio of the long-short portfolios.

4.2.1 Size factor analysis

When it comes to the size factor, there seems to be a discernable difference between the tech and non-tech sample. Looking at the main results table, the returns produced by the long-short using the tech sample is quite a lot higher than the portfolio using the non-tech, and looking at the T statistic of both, these suggest that small companies produce higher returns than large ones at a 5% significance level when it comes to the tech sector, while for the non-tech sample, the size factor was not statistically significant in this test. This is echoed by the alpha column, indicating significant alpha being generated by the tech sample, while the alpha of the non-tech not being significant. These results could be due to the construction of the long-short portfolio being constructed the same way across factors. The volatilities of both long-short portfolios are close to each other, and as such the Sharpe ratio is a fair lot higher for the tech-portfolio.

4.2.2 Value factor analysis

Looking at the results of the value factor, the average returns as well as the alphas are high both for tech and non-tech. These results seem to be highly significant as well according to the T-statistic for these portfolios, being significant at the 1% significance level. Both the average monthly returns and their standard deviations are higher for the tech sample, however, which would be a reasonable relation according to the CAPM. Looking at the Sharpe ratio however, the non-tech sample provides a higher return to risk ratio due to the high volatility of the tech sample.

4.2.3 Momentum factor analysis

The momentum factor results show the non-tech sample long-short portfolio providing higher average monthly returns than the tech one. This, in addition to the lower volatility of the non-tech sample gives the non-tech portfolio a far better Sharpe-ratio. The T-statistic of these portfolios indicate that the factor does indeed create statistically significant positive returns at a very significant level, but only for the non-tech companies. This is also represented by the alpha generated.

4.2.4 Idiosyncratic risk factor analysis

The result for this factor continues the trend of the previous one when it comes to returns, presenting higher average monthly returns for the long-short portfolio when applied to the non-tech sample, while the tech sample shows higher volatility in the returns. The T-stat for the returns of the long-short for the non-tech sample indicates that there are significant abnormal returns made by the stocks with the lower idiosyncratic risk at a very significant level. This cannot be said for the tech sample however, where a T-stat of 0.8297 fails to indicate significant returns for the factor. Looking at the alpha however, it does show significant abnormal returns for both samples, at the 5% significance level for tech and 1% level for non-tech.

4.2.5 Illiquidity factor

Both the returns and volatility of the long-short portfolio are higher for the tech sample when it comes to this factor. The T-statistic of the long-shorts point to the portfolio producing significant positive returns for the tech sample, at a 5% significance level. For the non-tech however, the result fails to indicate significant returns at even a 10% significance level. Looking at the alpha values, we see both long-short portfolios for this factor producing alpha however, even though the tech portfolio shows the highest alpha.

4.2.6 Profitability factor

The long-short portfolio of the non-tech sample for the profitability factor does outperform the tech one, both in average return and lower volatility. The positive returns of the non-tech sample are significant even at a 1% significance level, while the returns of the tech long-short portfolio are significant at a 5% level. When looking at the alpha however, the tech sample long-short produces more alpha, while both samples generate alpha at the 1% significance level.

4.2.7 Investment factor

For this factor, the tech long-short portfolio outperforms the non-tech in terms of average returns by a fair amount, but once again, the volatility of the tech portfolio is higher. Looking at the p-value however, both samples produce positive returns using this factor at a significance level of 1%. The alpha generated reflects this with both samples producing alpha at a 1% significance level, being higher for the tech sample. The higher returns and higher volatility for the tech sample portfolio does outperform the results of the non-tech portfolio when risk adjusted, with the Sharpe Ratio being higher for the tech sample.

4.3 Difference portfolio results

This section presents a table of the differences between the sorted long-short portfolios of the tech versus the non-tech samples. These are measured by several statistics explained below the table.

	$\bar{R}_f^{diff}$ (in %)	$H_0: \bar{R}_f^{diff} = 0$ (p-value)	α_f^{diff} (in %)	$H_0: \alpha_f^{diff} = 0$ (p-value)	SR_f^{diff}	$H_0: SR_f^{diff} = 0$ (p-value)
Size	0.50***	0.002	0.49***	0.002	0.26***	0.005
Book To Market	0.32**	0.011	0.37***	0.004	0.14	0.410
Momentum	-0.49***	0.006	-0.53***	0.003	-0.45***	<0.001
Idiosyncratic Risk	-0.34**	0.025	-0.38**	0.016	-0.26***	0.005
Illiquidity	0.32**	0.042	0.28*	0.080	0.12	0.285
Profitability	-0.03	0.806	0.11	0.413	-0.34**	0.031
Investment	0.54***	<0.001	0.56***	<0.001	0.09	0.572

*Table 3. This table shows the results of one portfolio for each factor constructed by taking the tech minus the non-tech long-short portfolio for that factor. *Indicates significance at 10% level ** Indicates significance at 5% level *** Indicates significance at 1% level.*

The R diff or difference in returns comes from taking the returns of the sorted factor portfolio for the tech sample reduced by the returns of the non-tech factor portfolio used to compare the significance of the differences between the samples. The portfolio created in this way will be referred to as the "difference portfolio". The Rdiff P-value indicates the likelihood of getting the results presented by "Rdiff" or a more extreme one given that the null hypothesis is true, meaning that a lower value indicates a more significant result for the difference between returns not being zero.

The alpha diff is as mentioned in the previous section the abnormal returns generated above what is predicted by the capital asset pricing model or CAPM, in this case by the difference portfolio. The p-value of the alpha diff is also presented, and in the same way as explained previously indicates the likelihood of the result presented or a more extreme one given that the null hypothesis is true.

Finally, the difference in the Sharpe ratios is presented, indicating the risk-adjusted returns of the difference portfolio. This is roughly speaking an indication of how much return you get for the risk you take on and could be used to measure the soundness of an investment.
In this table, a positive "SRdiff" indicates that the tech sample provides better risk-adjusted returns, while a negative value indicates the superiority of the non-tech long-short portfolio in providing risk-adjusted returns.

For the Sharpe ratio difference, a hypothesis test was conducted (see section 3.5.2 in the methodology chapter for details). The p-value from this test is presented in this table and should be interpreted as the likelihood of getting the result presented in "SRdiff" or an even more extreme one, given the null hypothesis that there is no difference in Sharpe ratios between the sample factor portfolios. This once again means that a low p-value indicates a significant result.

4.3.1 Size factor analysis

From Table 3, the difference in monthly returns is rather large as expected, more interestingly, looking at the p-value suggests that this difference is statistically significant at even a 1% significance level. The same is true when looking at the alpha to check against the CAPM.

From the HAC inference results, the P-value of below 0.05 indicates that the Sharpe ratios are indeed different at a significance level of 5%, which implies that the tech sample provides better risk adjusted returns for this factor.

4.3.2 Value factor analysis

The return difference appears to be significant for the difference portfolio, as does the alpha, the return at a 5% significance level and the alpha at 1%. Looking at the high p-value from the HAC test it cannot be concluded that there is a difference in risk-adjusted returns.

4.3.3 Momentum factor analysis

The difference portfolio for momentum is showing statistically significant higher returns for the non-tech sample by the negative returns of the portfolios (due to the nature of its construction where the return of the non-tech is taken from the return of the tech). The same can be said for the alpha, showing significant abnormal returns at a 1% significance level, just like the returns. The P-value for the HAC test for difference in Sharpe ratios also indicates that the difference in risk-adjusted returns is statistically significant with the non-tech sample providing superior risk-adjusted returns.

4.3.4 Idiosyncratic risk factor analysis

Looking at the difference portfolio, the p-value for the returns would indicate that the difference between non-tech and tech returns for the factor are statistically significant at the 5% level, with the alpha being significant at the same significance level and roughly the same level of returns. The Sharpe ratio for the long-short is as expected higher for the non-tech sample and looking at the P-value of the HAC test, the difference is statistically significant at the 1% level.

4.3.5 Illiquidity factor

Having a look at the difference portfolio, the returns of the long-short seem to be stronger in the tech sample at a 5% significance level. When looking at the alpha, it is also significant, but at a significance level of 10%. Looking at the Sharpe ratios however, while the tech long-short portfolio does produce a higher Sharpe ratio, the difference does not seem to be statistically significant in this test.

4.3.6 Profitability factor

The results for the difference portfolio suggest as expected that the non-tech outperforms the tech in terms of returns, but not by a statistically significant amount, leading to not being able to falsify the null hypothesis of the two providing similar returns. Interestingly, the alpha generated is positive, so when compared to the predictions of the CAPM, there are some weak abnormal returns favoring the tech sample, but not that are statistically significant at any reasonable level.

As for the Sharpe ratio, as expected following the return discussion, the Sharpe ratio is higher for the non-tech than the tech, and looking at the P-value of the HAC inference test, it can be concluded that this difference is indeed statistically significant at a 1% significance level, leading to the conclusion that the risk-adjusted returns are higher for the non-tech when using this factor, even if the absolute returns are not.

4.3.7 Investment factor

The difference portfolio confirms the tech sample outperforming the non-tech portfolio in terms of average monthly return and shows that this difference is statistically significant at a 1% significance level. This is also true for the alpha measure, which also proves true at a 1% significance level. For the Sharpe ratios, the non-tech long-short portfolio outperforms the tech one due to the tech having higher volatility. Looking at the P-value of the HAC-test however, this difference does not seem to be statistically significant at any relevant significance level.

From these results it can be deducted that the tech sample produces higher returns when sorting by the investment factor, and that it cannot be concluded that the non-tech provides higher risk-adjusted returns.

4.3.8 General analysis

For all factors except the size factor, the tech sample long-short portfolios had higher volatility than its non-tech counterpart. This higher volatility only came with higher average monthly returns four out of seven times.

4.4 Alternative results

This section introduces alternative main and difference tables, showing the same results as above but with the difference that the portfolios were value-weighted, meaning that each stock was allocated according to the size of its market cap. In other words, the larger the market capitalization of the stock, the more of the portfolio’s total wealth was put into this stock.

4.4.1 Alternative Main table

Factor VW	$\bar{R}_f^j$ (in %)	$H_0: \bar{R}_f^j = 0$ (p-value)	α_f^j $(in\ \%)$	$H_0: \alpha_f^j = 0$ (p-value)	$SD\left(R_{f,t}^j\right)$ (in %)	SR_f^j
Size Tech	0.21	0.484	0.07	0.821	6.75	0.11
Size Non-tech	-0.18	0.306	-0.12	0.520	4.03	-0.16
BM Tech	0.19	0.357	0.27	0.193	4.62	0.14
BM Non-Tech	0.15	0.263	0.19	0.161	2.91	0.17
Mom Tech	0.68**	0.027	0.94***	0.002	6.87	0.34
Mom Non-tech	0.48**	0.033	0.68***	0.002	4.98	0.33
Idio Tech	0.80**	0.012	1.33***	<0.001	7.11	0.39
Idio Non-tech	0.75***	0.002	1.17***	<0.001	5.47	0.48
Illiq Tech	0.23	0.381	0.07	0.781	5.81	0.14
Illiq Non-Tech	-0.02	0.907	0.10	0.536	3.48	-0.02
Profit Tech	0.28	0.253	0.66***	0.003	5.39	0.18
Profit Non-Tech	0.27**	0.033	0.42***	<0.001	2.81	0.33
Investment Tech	0.33	0.123	0.44**	0.038	4.71	0.24
Investment Non-Tech	0.16	0.107	0.29***	0.002	2.21	0.25

*Table 4. Value Weighted Tech and non-tech results for the long-short portfolio of each factor including return, alpha, standard deviation, and Sharpe ratio. *Indicates significance at a 10% level ** Indicates significance at 5% level *** Indicates significance at 1% level.*

Looking at this alternative main table, there are a number of differences. To name a few, the size and value factors failed to be significant predictors of returns, momentum was a stronger predictor for the tech sample and profit and investment had little significance for returns, while still being strong predictors of alpha.

4.4.2 Alternative Difference table

	$\bar{R}_f^{diff}$ (in %)	$H_0: \bar{R}_f^{diff} = 0$ (p-value)	α_f^{diff} (in %)	$H_0: \alpha_f^{diff} = 0$ (p-value)	SR_f^{diff}	$H_0: SR_f^{diff} = 0$ (p-value)
Size	0.40**	0.037	0.19	0.310	0.27**	0.012
Book To Market	0.04	0.825	0.09	0.671	-0.03	0.866
Momentum	0.21	0.403	0.26	0.302	0.01	0.929
Idiosyncratic Risk	0.05	0.822	0.16	0.484	-0.08	0.520
Illiquidity	0.25	0.226	-0.02	0.903	0.15	0.308
Profitability	0.01	0.973	0.23	0.246	-0.15	0.359
Investment	0.17	0.438	0.15	0.495	-0.01	0.961

*Table 5. This table shows the results of one portfolio for each factor constructed by taking the tech minus the non-tech long-short portfolio for that factor. *Indicates significance at a 10% level ** Indicates significance at 5% level *** Indicates significance at 1% level.*

Worth noting in this table is among other things that the only significant difference in Sharpe ratio was for the size factor, for other factors neither the tech nor non-tech samples provided better risk-adjusted returns than the other sample.

5. Conclusions

5.1 Research questions

I) For what factors does a portfolio of tech stocks utilizing a factor strategy produce abnormal returns?

For the size factor, it was concluded that the stocks of smaller companies did outperform the stocks of larger companies at a 5% significance level. This conflicts with CAPM according to which only increased levels of systematic risk should predict higher returns, whereas the size of a company should not. It is however congruent with previous research that has found the factor significant for the market as a whole (Fama & French, 1992). This is echoed by the alpha value also being significant at 5%.

The second factor found to produce significant returns at a 5% significance level was the profitability factor. The illiquidity factor was also found to produce significant returns at a 5% significance level, and the value and investment factors produced positive returns at even a 1% significance level. For the alpha values for these factors on tech, the alpha generated was found to be either equally as or more significant than the returns measure, further supporting a break from the assumptions of the CAPM.

For the idiosyncratic risk or low-risk factor, it could not be concluded at any significance level that abnormal returns were produced and the same was true for the momentum factor. However, when using the alpha measurement, the idiosyncratic risk was found to produce abnormal returns at a 5% significance level.

The results of these two factors indicate that for the tech sample specifically, the idiosyncratic risk factor has some ability to predict abnormal returns, while the momentum factor has no significant ability to predict abnormal returns.

II) How do those abnormal returns differ from a portfolio of non-tech stocks using the same strategy?

Looking at the non-tech sample, the factors did not give the same results, indicating a range of differences. The value, momentum, profitability, and investment factor all produced statistically significant abnormal returns at a 1% significance level, while the low-risk factor returns were significant at a 5% significance level. These are all as previously mentioned indications that the CAPM is not valid in the sense that one can achieve higher returns by sorting by the factor variables and not only by taking on more risk. Looking at the alpha results, the difference from the returns measure is the low-risk factor showing abnormal returns at a 1% significance level and the illiquidity showing abnormal returns at a 1% significance level, showing that there is indeed some merit in using this factor for non-tech as well.

Looking at the size factor, one of the possible reasons for the low significance of the returns could be the way the long-short portfolios were constructed, using a 30-40-30 split. The original size sorting done by Fama & French took the returns of the 10% smallest reduced by the average of the 90% that were larger, while this paper went for consistency in the formation of the portfolios.

Considering the differences between these and the tech results, the indication is that the average tech returns are larger for the size factor and investment factor at a 1% significance level and for the value and illiquidity factors they are larger at a 5% significance level. For the momentum factor the non-tech sample provided superior returns at a 1% significance level and for the low-risk factor, the non-tech sample produced higher returns at a 5% significance level. For the profitability factor, the returns leaned towards being higher for non-tech, but no difference could be proven through the T-test at any relevant significance level.

Looking at the results from a broader perspective, 4 out of 6 significant results for differences showed the tech sample producing more returns. If the CAPM is to be believed, this would come with higher risk, and looking at previous research, several papers have argued for the higher risk of tech firms over their lower tech counterparts (Shaker Ahmed & Alhadab, 2020)Having a look at the results table in this paper, this does appear to be true for this paper as well, for all factors except the size factor portfolios. This provides a good transition to the next research question, where the paper explores the risk-adjusted returns.

III) What is the difference for risk adjusted returns?

For this section, the risk adjusted returns were measured with the use of the Sharpe ratio. This was done in order to look at whether the higher risk associated with the tech sector also provided higher returns to compensate.

In the main results table, the Sharpe ratio is higher for the non-tech portfolio for the momentum, low-risk and profitability factors, while being higher for the tech portfolio for the value, size, illiquidity and investment factors. These results would indicate that for the most part, when taking the risk taken into account, tech portfolios performed better. There must be a check for statistical significance however for the sake of robustness, and so the HAC inference test was run to check if the differences in Sharpe ratio were statistically significant. For the value factor, the higher Sharpe ratio for the non-tech sample was not statistically significant at any reasonable significance level, indicating that the true difference in Sharpe ratios could be zero and the higher returns could in fact make up for the higher risk of the tech portfolio. This would indicate that one could choose to invest in the tech industry with the help of the value factor over the rest of the market for the higher return and higher risk profile of the investment without making a risk-adjusted worse investment decision. The same is true for the investment factor, where the non-tech sample Sharpe ratio was higher, but was not statistically significant, and so the possibility of the Sharpe ratio being the same cannot be rejected.

Then there is the case where the tech portfolio Sharpe ratio was higher, as is the case for the illiquidity factor. The illiquidity factor showed higher returns for the tech portfolio, and while the volatility was also higher, the Sharpe ratio was still higher for the tech portfolio than the non-tech one. This was not statistically significant for this factor either however, and so the null hypothesis of no difference in the Sharpe ratio cannot be rejected once again, and so an investor might choose either to invest in the tech or the rest of the market depending on preference without making a worse decision Sharpe-wise.

Now for the factors where the non-tech had significantly higher returns than the tech, namely the momentum and low-risk factors. For these two factors, the Sharpe ratio was higher for the non-tech portfolio. This was also confirmed to be statistically significant through the HAC inference test for both at above the 1% significance level.

This would indicate that for these factors, it is always a better investment to invest in the rest of the market compared to the tech sector, as long as the investor does not prefer higher risk for no reward in return. This result is quite interesting, as it stands in conflict with earlier research that has shown the momentum factor in particular to always reward higher returns for the high-tech sector (Shaker Ahmed & Alhadab, 2020). This could be due to a difference in stock selection or portfolio formation, as even though this paper aimed at using previous research to help with stock selection, the nature of how one defines tech or high-tech is not set in stone.

For the profitability factor, while it is indicated that the returns are higher for the non-tech portfolio, this is not statistically significant at any reasonable level, and so the Sharpe ratio comparison also loses relevancy. Lastly, there is the size factor. For this factor, both the returns as well as the Sharpe ratio was higher for the tech portfolio. The Sharpe ratio difference was also confirmed to be statistically significant at a 1% significance level. This would indicate that for a size-based strategy, investors would do better investing in the tech sector as opposed to non-tech companies.

5.2 Summary

To summarize this chapter, the higher volatility of the tech sector was reaffirmed for the most part, and for several factors, the tech sector did provide a higher average return, though often at the cost of higher volatility. Through Sharpe ratio difference tests, for three out of the seven factors the Sharpe ratio was not significantly different for tech or non-tech and an investor could choose to invest in the tech sector for a higher risk and higher reward profile. For two of the factors the non-tech stocks simply provided better risk-adjusted returns and for one factor the tech portfolio provided superior risk-adjusted returns.

5.3 Suggestions for further research

There seems to be many areas to look at further when it comes to factor research, as well as when it comes to the technology sector. While the authors hope that this paper can contribute some knowledge to the field, the importance of the sector merits more attention. Multi-factor portfolios including double sorting is something that was deemed out of the scope of this paper but would be interesting to see for example, as well as differences in weighing strategies, and checking returns for more specific sectors within tech, are only some of the ideas that are close by and could prove interesting for future research. While different explanations have been suggested before, the increased volatility in the tech sector and suggestions to deal with it are also always interesting.

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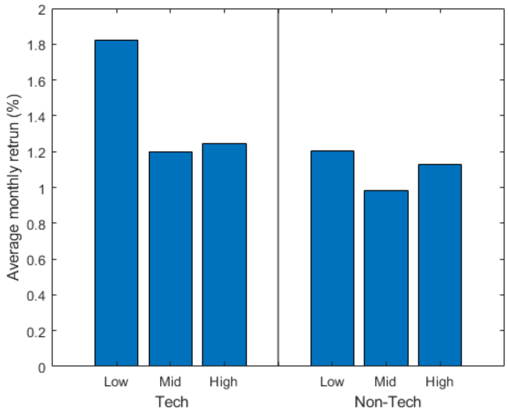
Appendix

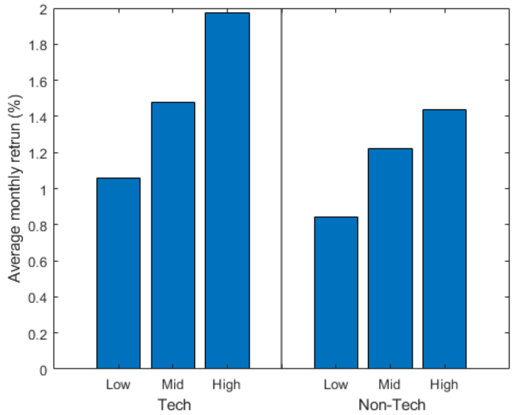
A1. Graphs

This section includes the yearly average returns of the 3 portfolios used to create the long-short portfolios (low – neutral – high) of each factor applied on the 2 samples tech and non-tech, presented in bar graph form for easy comparison.

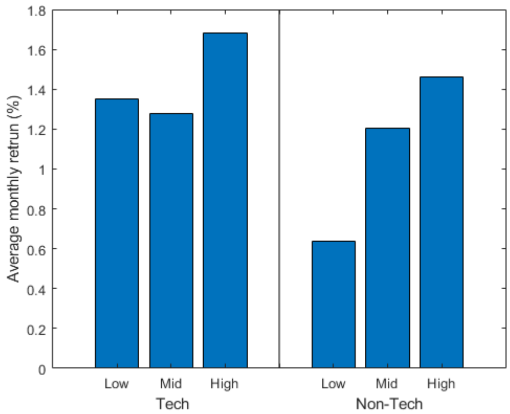
Equal-weighted



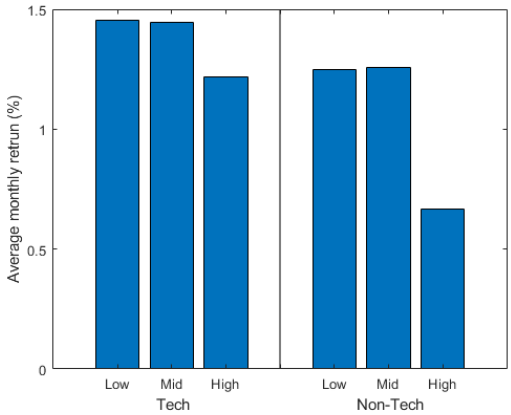
Size factor portfolios



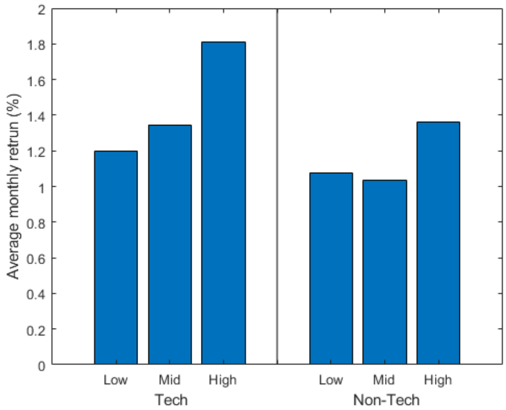
Value factor portfolios



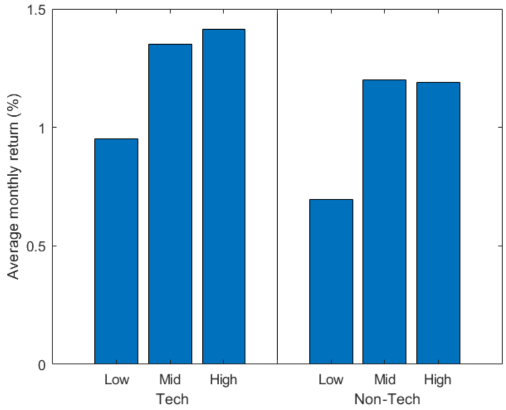
Momentum factor portfolios



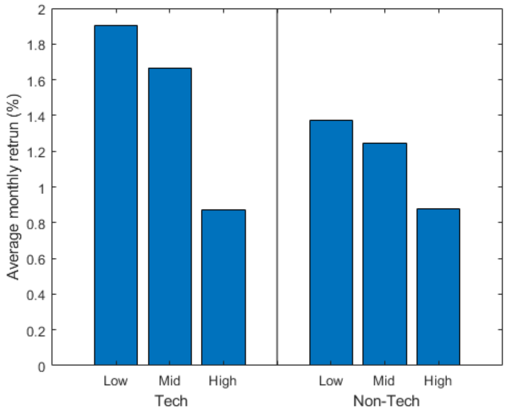
Idiosyncratic risk factor portfolios



Illiquidity factor portfolios



Profitability factor portfolios



Idiosyncratic risk factor portfolios, tech

A2. Original idea formulation

Factor investing in tech

Inspiring paper: Factor Investing in Emerging Market Credits by Lennart Dekker, Patrick Houweling, Frederik Muskens :: SSRN

Inspired by the above linked factor investing paper, one of our proposed subjects is researching the returns profile of portfolios constructed using a multi-factor model, selecting out of specifically tech stocks.

Tech stocks, especially those that come from different types of startups are notoriously hard to price/value correctly, which makes it interesting to know how well factor-based investing does in this segment of companies. The time period of interest would be fairly recently and backwards as long as data is available and comparable.

The research would comprise forming multi-factor-based portfolios including classic factors such as value-growth, size as well as popular ones such as momentum and others. This can then be compared to the market return, and/or equally/market-size weighted portfolios, in order to check what factors can be used in a tech investment strategy.

The inspiration for this idea came from the paper “Factor Investing in Emerging Market Credits” (Robeco, 2021) where factor investing is applied to Emerging markets and corporate bonds, showing generated in different setups.

While the original idea is mainly aimed at the tech sector as an industry, it can also be homed in on a specific region, such as the Nordic/Swedish tech sector for example. The data should be readily available as it would be made up of mainly stock data available from Bloomberg among others.