UNIVERSITY OF TURKU

ABSTRACT

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Abstract

Relevancy of traditional value investing strategies have been questioned after a long period of underperformance. The book-to-market ratio has not been performing in almost four decades in the US large cap space. Bulk of the academic value investing research is done based on book-to-market multiple, rarely wide set of multiples is studied and questions like "Do enterprise value-based multiples work better than market capitalization-based multiples?" or "Do forward-looking multiple perform better than past-looking multiples?" are not asked.

Growing body value investing research is suggesting that enterprise value-based multiples might work better than the traditional multiples like book-to-market or earnings-to-price ratios. Some studies have found out that value investing strategies perform better when the focus is on a specific sector or industry. Prior research has not explicitly focused on technology sector.

The main objective of this paper is to determine which value investing strategies perform the best in the Nordic technology sector measured by raw and risk-adjusted returns. To gain more insight, the characteristics of the best strategies are studies as well. A portfolio method is applied to study the value investing strategies in the Nordic technology sector from the 31st of March 2006 to 1st of April 2021. The biggest sample contains 332 unique firms. The main performance measures are technology sector adjusted returns, Sharpe ratio, Sortino ratio, Sortino_F ratio and Fama-French three-factor alpha.

The results provide evidence that value investing strategies can be profitable also in the technology sector even though the overall Nordic technology sector performed extremely well generating 15.5% annual return. The best performing multiple was operating-adjusted EBITDA/EV measured by all raw and risk-adjusted returns. Top quintile EBITDA/EV portfolio generated 24.0% CAGR, 7.0% annual technology sector-adjusted return and 18.7% three-factor alpha. Second best multiples were CF/EV and CF/P. Traditional B/P ratio performed poorly. Enterprise value-based multiples outperformed market-capitalization in almost all the cases. Forward-looking multiples outperformed corresponding past-looking multiples in almost all the cases. Some evidence was got that 12-month forward-looking earnings-to-enterprise value would the best performing multiple in the space with larger and more liquid stocks.

Key words	Lorem, ipsum, major

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Tiivistelmä

Arvosijoitusstrategioiden toimivuus on kyseenalaistettu viime vuosina pitkän aliperformointijakson jälkeen. Klassinen B/P ratio ei ole tuottanut ylituottoa lähes neljään vuosikymmeneen USA:n suurten yritysten kentässä. Kuitenkin suurin osa arvosijoitustutkimuksesta tehdään yhä perustuen klassiseen B/P lukuun. Harvoin laaja kirjo erilaisia multippeleita on ollut tutkimuksen kohteena ja kysymykset kuten ”Toimiiko yritysarvopohjaiset multippelit paremmin kuin markkina-arvopohjaiset multippelit? tai ”Toimivatko eteenpäin katsovat multippelit paremmin kuin taaksepäin katsovat multippelit?” on jätetty kysymättä.

Kasvava joukko arvosijoitustutkimusta viittaakin siihen, että yritysarvopohjaiset multippelit kuten EBITDA/EV voisivat toimia paremmin kuin perinteiset multippelit. Jotkin tutkimukset ovat löytäneet viitteitä, että arvosijoitusstrategiat toimivat paremmin, kun ne kohdistuvat jollekin tietylle toimialalle tai sektorille. Aikaisempaa tutkimusta arvosijoittamisesta kohdistuen juuri teknologiasektoriin ei löytynyt.

Tämän tutkimuksen päätavoite on määrittää mitkä arvosijoitusstrategiat toimivat parhaiten teknologiasektorilla raaoilla ja riskikorjatuilla tuotoilla mitaten. Portfoliometodia käytetään tutkimuksessa aikavälillä 31.3.2006 – 1.4.2021. Suurin otos sisältää 332 uniikkia yhtiötä. Päämittareina käytetään teknologiasektorioikaistua tuottoa, Sharpe ratiota, Sortino ratiota, Sortino_F ratiota ja Fama-French 3-faktorialfaa.

Tulokset tuottavat todisteita siitä, että arvosijoitusstrategiat toimivat myös Pohjoismaiden teknologiasektorilla, vaikka koko teknologiasektoriportfolio tuotti todella hyvin, tuottaen 15,5% annualisoidun tuoton tarkastelujaksolla. Parhaiten performoiva multippeli oli operatiivisen tuloksen osalta oikaistu EBITDA/EV, puhtailla ja riskikorjatuilla tuotoilla mitattuna. Halvin EBITDA/EV kvintiili tuotti 24,0% annualisoidun tuoton, 7,0% teknologiasektorioikaistun tuoton ja vuosittaisen 18.7% kolmifaktorialfan. Seuraavaksi parhaat multippelit olivat CF/EV ja CF/P. Perinteinen B/P multippeli oli yksi heikoimmista. Yritysarvopohjaiset multippelit tuottivat paremmin kuin markkina-arvopohjaiset. Eteenpäin katsovat multippelit toimivat paremmin kuin taaksepäin katsovat multippelit. Tulokset tuottivat todisteita siitä, että 12 kuukautta eteenpäin katsova E/EV (nettotulos-suhteessa-yritysarvoon) olisi kaikista paras multippeli likvidimpien ja suurempien yritysten otoksessa.

Avainsanat	Lorem, ipsum, Suomi

UNIVERSITY OF TURKU
Turku School of Economics

VALUE INVESTING STRATEGIES IN THE TECHNOLOGY SECTOR

Empirical study in the Nordic technology sector

Master's Thesis
in Accounting and Finance

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Prof. Mika Vaihekoski

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1 INTRODUCTION

1.1 Motivation and background

In the recent years the debate regarding the value investing relevancy have heated up in the investing community, and headlines like *Is value investing dead?* by Neo (2021) seem to be a common occurrence. Articles criticizing value investing most often focus on the traditional book-to-market ratio strategies proposed first by Fama and French (1993). For example, Blitz and Hanauer (2021) show that traditional value premium has not been outperforming almost for four decades in the US large cap space. However, value investing is still widely popular, and often the applied strategies are more sophisticated than just picking stocks mechanically based on high nook-to-market value. Though, mechanical strategies can also be improved as for example Blitz and Hanauer (2021) and Davydov et al. (2016) argue. At the same time, when the traditional value investing strategies have the most doubters, the stock markets have experienced a long bull market and the market behavior exhibits classic bubble signs, fueled by negative interest rates and the massive liquidity provided by the central banks. It is a perfect time to take an updated look at the value investing strategies.

Academic studies rarely focus on specific industry or have a wide set of multiples. Often the multiples chosen are the traditional ones. For example, the enterprise value-based (EV) multiples like *EBITDA/EV* (EBITDA-to-EV) or *S/EBIT* (sales-to-EV) are rarely paid attention compared to the market capitalization-based multiples like *E/P* (earnings-to-price) and *B/M.* In fact, in many studies that incorporate EV-based multiples, they find that EV-based multiples outperform the other multiples (for example, Pätäri et al. 2016; Grey and Vogel (2012)). Forward-looking multiples are also ignored systemically. Although, most of the investors would agree that the future profits, cash flows and sales are more important than the past ones, still it is rare that academic studies study the forward-looking multiples in the value investing literature. Especially it is rare, that a portfolio method has been used to study these strategies. For example, Liu et al. (2002) and Scheiner (2009) show evidence that forward-looking multiples outperform the past-looking multiples when measured the valuation accuracy.

Many technology sectors have generated high returns in the 2010s. For example, Nasdaq 100 index has generated compounding annual growth rate (CAGR) of 19.1% between 4th of January 2010 and 1st of April 2021 and the Nordic technology sector examined in this research generated 21.3% CAGR in the same period. The returns are so high that the investors must have systematically underestimated the potential of these technology sector companies. No academic studies could be found that studied value investing strategies in the technology sector. This may be due that there are some key differences in the technology sector which are sometimes hard to consider with the traditional accounting methods, and for example the traditional value signal book-to-market ratio is thought not to work properly among the immature companies. And the accounting information is basically the information that most of the investors and academics can use. Some key questions revolve around intangible asset valuation, R&D-expenses and Marketing and Sales expenses. IFRS-standards are being developed to make the accounting standards work also in the modern economy. Under IFRS-standards companies can treat development costs as investments and activate them to their balance sheets but the terms are strict, and they require a lot of subjectivity. The subjectivity then makes the financial statements less valuable as companies' practices differ from each other.

Since the development of personal computers and internet in 1980s and especially in the 21st century, the knowledge has become the main source of value generation in many business sectors, this is especially true in the technology sector. The success of many firms is not tied anymore only in the physical tangible assets but rather in the intangible assets like brands and software. Investments in the research and development to create intangible assets has become one of the success factors. Already in 2006 Hulten and Hao (2008) found that book value of equity explained only 31 percent of the market capitalization in the research & development intensive sectors with a sample of 617 companies. They adjusted the book values with an estimation of capitalized intangible assets created by research & development expenses and a part of marketing & sales expenses. When the estimates of the capitalized cost of the intangible assets were added to the balance sheet of these companies, the fraction of the market capitalization explained by this augmented measure of book value rose to 75 percent. The problematic effect from the valuation point of view arising from the value creation through intangible assets extends also into the financial statements as the profits are distressed because the investments are expensed and not capitalized. This makes the current profits look sometimes lower than they should.

This research aims to study wide set of valuations multiples that can be extracted from the Refinitiv Eikon database. The questions that have been ignored largely by the academic literature are studied. The aim is to consider questions which the practitioners should also consider in their daily work. For example: Should forward-looking or past-looking valuation multiples given more value; Should enterprise value-based or market capitalization-based multiples be used? The aim of the research is to produce results that can be practically applied.

1.2 Research objectives

The main objective of this research is to test which value investing strategies generate highest stock-market risk-adjusted returns in the Nordic technology sector. Furthermore, the tests are also conducted to examine whether incorporating momentum strategies can improve the pure value strategies. Third objective is to investigate whether enterprise value-based multiples outperform than market capitalization-based multiples. Fourth objective is to find whether forward-looking multiples outperform past-looking multiples and find which ones perform the best. Fifth objective is to investigate whether using operating-adjusted multiples is more profitable than using the reported multiples.

The research objectives of this study are reached through an empirical analysis as follows. First, the pure-play value portfolios are constructed, and the raw and risk-adjusted returns of the portfolios are investigated by comparing compound annual growth rates, market-adjusted returns, Sharpe ratios, Sortino ratios and Sortino_F ratios. Next, the combination portfolios incorporating momentum are constructed based on the performance of the value strategies and the correlation between a value and the momentum strategy. The same performance measures are evaluated for the combination portfolios. Next, the same process is repeated with the forward-looking multiples. In the following section, Fama and French (1992) three-factor model is used to measure abnormal returns to control whether the possible outperformance of the different strategies can be explained by the asset pricing model's factors. Next, to add further dimension to the performance of the portfolios, bull and bear market periods are investigated separately.

To have the most stocks for the different multiples available, three different main group samples are created: main sample, momentum sample and forward-looking samples. Furthermore, forward-looking samples are divided into four sub-samples: EBIT, EBITDA, E(Adj.) and Sales samples. The samples are formed based on the financial metrics that can be found in the Refinitiv Eikon database. The motivation for the further subsampling of the forward-looking sample is that the focus in these samples is on whether the portfolios based on forward-looking multiples perform better compared to the past-looking multiples and by subsampling we can have the largest possible sample size for each multiple.

Large set of different valuation multiples are investigated. This is contrary to the most academic studies which focus often just on few multiples and to the trailing multiples. The chosen valuation multiples are based on the multiples that are used in the academic literature as well as used by the practitioners. Furthermore, to fulfil the objective of the study another set of multiples are added which have gotten little to no attention at all in the academic studies. These multiples include for example forward-looking multiples as well as E/EV (earnings-to-enterprise value) and B/EV (book value-to-enterprise value). Scheiner (2007) conducted a study with an extensive set of multiples. He found for example that forward-looking multiples perform better than past-looking in general. However, he measured the valuation accuracy of the multiples and not the predictive power. As extensive set of multiples with portfolio method as in this study is not studied before in the academic literature at least to the authors' best knowledge. Unfortunately, the multiples based on gross profit or R&D expenses are not studied. Gross profit multiples are not investigated because the quality of the gross profit data was very low in the database. Multiples incorporating R&D expenses are left out this study because the sample sizes would have become too small.

1.3 The structure and limitations

The thesis is divided into six sections: introduction, value investing, valuation in the technology sector, data and methodology, empirical results, and conclusions. Value investing and valuation in the technology sector are examined trough the literature review. The objective is to combine academic and practitioners' point of view as much as possible. This will be reached by focusing on the questions in the academic research that practitioners consider in their everyday work. Value investing section's empirical framework is built around, equity valuation using multiples, value premium, value investing strategies and combining value and momentum strategies. The aim is to develop the value investing strategies that used in the empirical study. Valuation in the technology sector focuses on two main concerns, general things investors should consider in the technology sector and valuation of loss-making growth companies. These are important consideration going into the empirical section.

The data and methodology section will discuss the used methods used in this thesis. The section is divided into data and definitions, portfolio construction and performance evaluation. All the important measures and methods used in the empirical results are explained in this section. All the abbreviations are also explained is this section. Empirical results section discusses the empirical findings extensively. The results are examined in three different sample groups. The performances of the all the strategies are also studied separately during the bull and bear markets. Extensive set of strategies is investigated thoroughly. In the conclusion section the findings are compiled, and the implications and practical use-cases of the research are discussed.

The data will be limited to the technology sector of Nordic listed companies (Finland, Sweden, Norway, and Denmark), First North Finland technology sector and some selected technology intensive companies from the Helsinki Stock Market which don't belong to the technology sector. The data is gathered from the Refinitiv Eikon database, the data gathered from the database is trusted to be high-quality. The total main sample consists of 332 unique companies. Multiples which incorporate research & development costs, or which are based on gross profit are excluded. The gross profit measures in the samples were too low-quality data in the Refinitiv Eikon database and the sample sizes including multiples with research & development costs would have become too small. Also, the marketing and sales expenses will be left out this study even though they also could be considered as an investment in the technology sector according to the literature. The marketing and sales expenses will be left out of the study because the data from Refinitiv Eikon does not separate them for most of the companies. This study will focus on equity valuation using multiples and other valuation methods will be considered only briefly.

2 VALUE INVESTING

2.1 Asset pricing models

According to Efficient Market Hypothesis (EMH) it is not possible for investors to obtain abnormal returns in relation to the risk that they carry. EMH states that the prices reflect all possible information available in the stock market, even the insider information, and that the stock prices react immediately to the new information. EMH is the foundation of the traditional finance theory, for example for the Capital Asset Pricing Model. The market efficiency can be divided into three levels: strong, semi-strong and weak efficiency. Strong efficiency is the level of efficiency, in which market prices reflect all the possible information. Semi-strong efficiency states that all the public information is reflected on the prices. Under the semi-strong efficiency neither fundamental nor technical analysis can be used to generate abnormal returns. Weak efficiency states that the prices reflect the past prices. Under the weak efficiency it is not possible to generate abnormal returns with technical analysis. (Fama 1970) Large branch of academic research agrees that the semi-strong level of efficiency exists in the stock markets. In the semi-strong efficient market, it would not be possible to generate abnormal returns following value investing strategies.

Capital Asset Pricing Model (CAPM), originally developed by Mossin (1966), Sharpe (1964) and Treynor and Lintner (1961) describes the relationship between systematic risk and expected return of the security. Two essential assumptions of the model are that investors are risk adverse and when choosing among investment portfolio options, they only care about the mean and variance of their returns. The CAPM can be used to valuate assets and calculate their expected return.

$$E(R_i) = R_f + \beta_i E(R_m - R_f),$$

where $E(R_i)$ is the expected return, R_f is the risk-free rate of interest, β_i is the beta of the asset and $E(R_m - R_f)$ is the market risk premium. CAPM describes the relation between systematic risk and an expected return for an asset. According to Capital Asset Pricing Model any excess return of an asset is directly proportional to its beta (risk). According to Rossi (2016) the CAPM is still widely used in important applications in finance like estimating the cost of capital for companies and evaluating the performance of managed portfolios. Despite the widespread use of the CAPM, its empirical results are mixed and tilted towards poor results. Rossi's (2016) literature review of the CAPM concludes that the original version's explanatory power is weak for the risk-return tradeoff and for the role that market risk plays in the determination of stocks' excess returns.

Fama and French (1992) introduced the factors of their influential three-factor asset pricing model. Three-factor model is developed upon CAPM. Fama and French (1992) found that their tests didn't support the prediction of CAPM, that stock returns on average are positively related to the market betas. Their study showed that univariate relations between average returns and leverage, E/P (earnings-to-price), size, and book-to-market equity are strong. They found that the negative relation between size and average return remains also in multivariate tests, and it is robust to the incorporation of other variables. The positive relation between average returns and book-to-market equity also remains when adding other variables. Their study found that book-to-market equity was persistently stronger in explaining the average returns than size. The main finding of the study was that the combination of size and book-to-market equity effectively absorbs the role of E/P and leverage in explaining the average stock returns. These findings suggest that the risk in stock returns is multidimensional. The three-factor model will be the main method to evaluate abnormal returns in this study.

Fama and French (1993) introduced formally the three-factor model as follows:

$$E(R_i) - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i(SMB) + h_i(HML),$$

where $E(R_i)$ is the expected return on asset i, R_f is the return on risk-free asset, $\beta_i(R_m - R_f)$ is the market risk premium, SMB is the size premium (small minus big) and HML is the value premium (high minus low).

Another factor for explaining stock returns that Fama and French (1993) didn't consider is momentum. Jegadeesh and Titman (1993) found that over the 1965 and 1989 period trading strategies that buy stocks that have performed well and sell stocks that have performed poorly realize significant abnormal returns over 3- to 12-month holding period. For instance, a strategy that picks stocks based on their past 6-month performance and holds them for 6 months achieved a compounded abnormal return of 12.01% yearly on average. Their evidence implies that the strong performance of the momentum strategies is not due higher systematic risk.

Carhart (1997) augmented the Fama-French three-factor model by adding Jegadeesh and Titman's (1993) one-year momentum anomaly to the model. The motivation for this was Fama and French (1993) three-factor model's inability to explain cross-sectional variation in momentum-sorted portfolio returns. Momentum factor PRIYR could be described as one-year momentum versus contrarian stocks. Carhart four-factor model is computed as follows:

$$E(R_i) - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i(SMB) + h_i(HML) + p_i PR1YR,$$

where *PR1YR* is the momentum factor (winners minus losers). Carhart (1997) four-factor model explained better stock returns than the Fama-French three-factor model. The model and investment expenses almost explained persistence in equity mutual funds' mean and risk-adjusted returns. Bello (2008) found that while Fama-French three-factor model has significantly more predictive power than CAPM, the Carhart four-factor is also a significant upgrade over the three-factor model in terms of predicting stock-mutual-fund returns. Relevantly for this study, Rehnby (2016) found similar evidence in the Swedish stock market. Although, he found that the four-factor model's edge over the three-factor model was smaller than what Bello (2008) found. Rehnby (2016) concluded that Carhart four factor model is the best for portfolio managers to implement on the Swedish stock market to measure abnormal returns. His results also suggest that all models have a low explanatory power during the volatile times in the markets.

Fama and French (2015) upgraded their model with two additional factors: profitability and investment factors. Based on the evidence shown by Novy-Marx (2013) and Titman, Wei, and Xie (2004) as well as others, that the three-factor model factors miss much of the variation in average returns related to profitability and investment. Fama and French five-factor model is computed as follows:

$$E(R_i) - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i(SMB) + h_i(HML) + r_i RMW + c_i CMA,$$

where *RMW* is the profitability factor (robust minus weak profitability) and *CMA* is the investment factor (robust minus weak profitability). Fama and French (2016) found that in the five-factor model HML becomes redundant in the US data sample in the 1963-2013 period. They believe that is due other factors, especially CMA. They estimated that the model explains between 71% and 94% of the cross-section variance of expected returns for size, book-to-market, profitability, and investment portfolios that they examined.

2.2 Equity Valuation using multiples

Pinto et al. (2019) split different valuation methods used by the professionals in five categories: a market multiples approach (MM), a present discounted value approach (DV), an asset based (AB), a (real) options approach (OP) and other approach (other). MM for example, is based on price-to-earnings ratios and other multiples. DV for example, is based on discounted forecasted future free cash flows, dividends, or other metrics. AB for example, is based on asset value or asset market values. OP methods use options models to value equity. They found that 92.8% of respondents use MM, 78.8% use DV, 61.4% use AB, 5% use OP and 12.7% use other methods. The percentage of the cases respondents use each approach (conditional frequency) was 68.6% for MM, 59.5% for DV, 36.8% for AB, 20.7% for OP and 58.1% for other. MM is the most used by the professionals and it is also the most widely applicable approach.

This study is about the market multiples approach, so the other valuation methods are not discussed in detail. Pinto et al. (2019) found in the further analysis of market multiples approach that P/E (price-to-any earnings metric) and enterprise value-based (EV) multiples were the most used ones with 88.1% and 76.7% of the respondents using them. They had also the highest conditional frequencies: 67.2% and 61.1%, respectively. However, it is good to note that EV multiples included all the possible EV multiples which covers quite a broad set of multiples compared to the other categories. Table 1 reports the summary of the used multiples and their conditional frequencies by the professionals. The third most popular category was P/B (price-to-some asset-based value) with 59.0% usage, fourth P/CF (price-to-some cash flow measure) with 57.2% and fifth P/S (price-to-sales or revenues) with 40.3%. However, P/CF was more widely applied with conditional frequency of 54.6% compared to P/B 44.8% and P/S 45.7%. D/P (dividend yield) was used by 35.5% of the respondents with 44.3% conditional frequency.

Table 1 Details of the market multiples approach used by the professionals (Pinto et al. 2019)

When you use a market multiples approach, which of the following ratios do you use? (N = 1,765)	Percent of respondents	Percentage of cases respondents use each approach (mean)
D/P (Dividend yield) or P/D (Price-to-dividend)	35.5	44.3
Enterprise value (EV) or firm value multiples (e.g., EV-to-EBITDA, EV-to- operating profit)	76.7	61.1
P/B (Price-to-book value, price-to-adjusted book value, book-to-market)	59.0	44.8
P/CF (Price to some measure of cash flow)	57.2	54.6
P/S (Price-to-sales or revenues)	40.3	45.7
P/E (Price to some measure of earnings)	88.1	67.2
Other ratios	11.6	58.5

Within P/E multiples forward-looking forecasted net income was the dominant choice as the preferred choice in the denominator within 61.1% of the respondents in the P/E category. Second was forecasted operating income with 20.1% and third trailing net income with only 8.8%. Within the EV category EBITDA was the dominant choice in the denominator with 88.3% of respondents using it, followed by free cash flow (21.2%), EBIT (19.2%), Revenue (16.6%) and other (5.6%). Interestingly for the technology sector, EV/Sales (revenues) seems to be used by only less than a third as many practitioners as P/S (Price-to-Sales). Within the P/CF category, free cash flow to equity was the preferred choice in the denominator with 32.2%, followed by free cash flow to firm (28.9%), operating cash flow (22.3%), EBITDA 12.7% and other (3.9%).

Milano et al. (2016) studied the most popular indicators of corporate operating performance in the US stock market technology sector. Their sample included 169 large technology companies. They tested which operational metrics had the highest correlation with the total shareholder returns over 3 year rolling periods between 2006 and 2015. The metrics that they chose were EBITDA margin, operating margin, gross margin, residual cash margin, gross business return, sales compound average growth rate (CAGR), return-on-equity (ROE) and change in residual cash earnings (RCE). RCE was their own metric which they developed for the study. Gross cash earnings are calculated as follows: EBITDAR (earnings before interest, taxes, depreciation, amortization, and research & development expenses) less Income tax expense. And from these gross cash earnings is deducted capital charge from gross operating assets (GOA). GOA is calculated by deducting operating liabilities from operating assets. In addition to the traditional accounting measures the operating assets include capitalized research & development expenses and capitalized operating leases from the last five years. Milano et al (2016) found that change in RCE explains best the total shareholder returns. Followed by ROE and sales CAGR. They found also that investors should focus more on absolute metrics like operating profit relative increase rather than operating margin improvement. Their results indicate that in the technology sector investors should also consider R&D expenses when valuing companies.

2.3 Value premium

According to Chan and Lakonishok (2004) academics had come largely into an agreement for the value premium existence in the market based on the accumulated weight of the evidence from the studies on the book-to-market effect and related anomalies. Academic community had come generally to agree that value investment strategies, on average, outperform growth investing strategies and the market. They found that even when considering the tech bubble, value investing strategies generated superior returns. The underlying reasons for the premium, however, are a subject for debate. Notably, Fama and French (1992) took the position of the efficient market hypothesis and their research indicated that the increased risk was behind the higher returns. Another explanation for the higher return stems from the behavioral finance. Lakonishok et al. (1994) argue that the higher returns are not generated by carrying higher risk but because the strategies exploit the suboptimal behavior of the average investor.

Fama and French (1992) found that there is a positive simple relation between average return and market beta in the NYSE stocks. They found that the positive simple relation between beta and average return disappeared during the more recent 1963 - 1990 period. Their evidence did not support the central prediction of the traditional model, that the average stock returns are positively related to market beta. They decided to look for alternative explanations like size, book-to-market, earnings-to-price (E/P) and leverage. Their work suggests that low book-to-market firms tend to be persistently poor performers relative to high book-to-market firms. They argue that from the efficient market hypothesis point of view high book-to-market value could be a sign of distress and investors rationally expect higher returns for carrying the risk of the distressed company. Interestingly they also found that higher E/P (earnings-to-price, the inverse of P/E-ratio) values did not have explanatory power for higher returns when controlling for the size- and book-to-market- factors. Their result suggests that the higher returns from low E/P stocks is due positive correlation between E/P and book-to-market, firms with high E/P tend to have high book-to-market ratios. Though, Fama and French leaned towards a rational explanation for the higher returns but they also admitted that it might be for the irrational over- and underreactions of the market.

According to Fama and French's (2012) results, the value premium was stronger in small-cap samples than in the larger-cap ones. Cakici and Tan (2014) results also confirm the higher value premium among the smaller companies compared to the large companies. They also found that value returns were higher when the liquidity was lower. In the Nordic markets, Cakici and Tan (2014) found that the value premium was stronger among the small caps in all four countries. Especially, in Finland and Denmark they found that the small cap value stocks outperformed by wide margin the large caps. In fact, in Finland the value factor for the large companies was negative.

Lakonishok et al. (1994) suggest that the superior returns from value investing are due the contrarian nature of the strategy. Value strategies are contrarian to "naïve" strategies followed by average investor. These "naive" strategies can possibly range from extrapolating historical earnings growth too far into the future, to assuming that a trend exists in the stock prices, overreacting to good and bad news, or to simply equating a well-run company as a good investment regardless of the stock price. Without a rational explanation some investors tend to get overly excited about some stocks that have done exceptionally well in the past and buy them up, so these "glamour" stocks that everyone knows become overpriced. In a similar fashion, investors can oversell stocks that have done badly in the past, and so these out-of-favor "value" stocks become underpriced. Contrarian bet against these kinds of investors who follow "naive" strategies. Value investors will outperform the market because they invest disproportionally in stocks that underpriced and avoid stocks that are overpriced. Lakonishok et al. (1994) also argue that value strategies are not fundamentally riskier, so the superior investing returns cannot be the result of higher risk carried.

Blitz and Hanauer (2021) provide evidence that classic HML value factor, introduced by Fama and French (1993), has not overperformed significantly during the last four decades. As can be seen from Figure 1, large cap HML factor has essentially been flat for the last four decades from the year 1980 to 2020. Small cap HML factor has still performed but it also falls almost flat in the last two decades especially after the bursting of the tech bubble. HML factor has still performed reasonably well, but it is important to consider that it is weighted 50% and 50% between the small and large cap factors, so large part of its performance is due ill-liquid small and micro-cap firms' performance. Blitz and Hanauer (2021) conclude that concerns over the disappearance of the traditional value premium, or at least serious impairment, are not unreasonable.

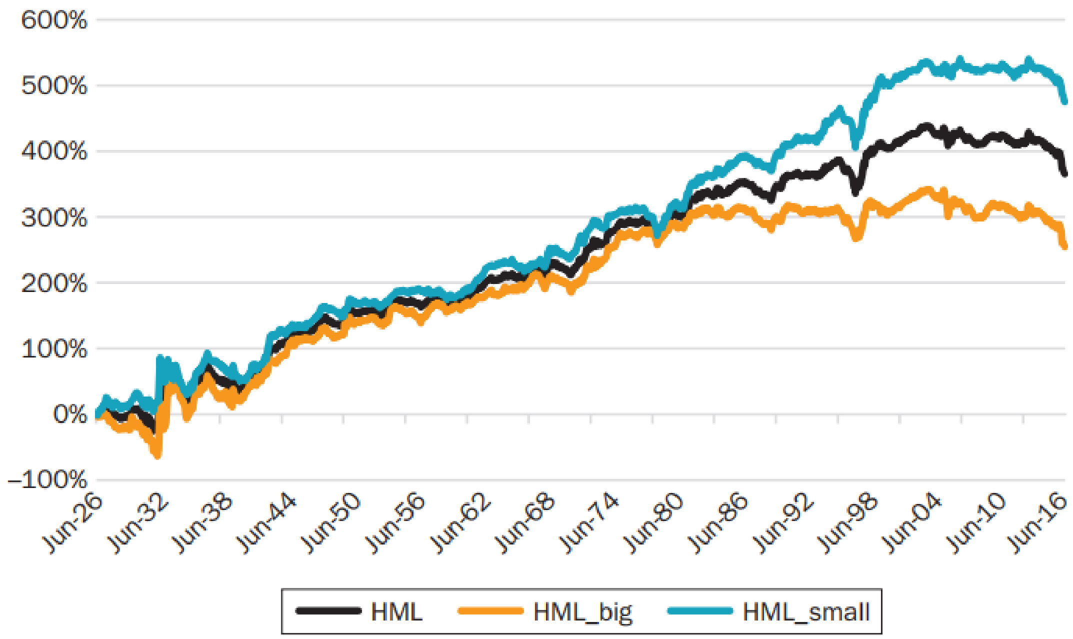

Figure 1 Cumulative return of HML value factor in the United States (Blitz and Hanauer 2021)

Blitz and Hanauer (2021) provide an alternative for the traditional HML value factor. They argue that the value premium can be resurrected by considering more sophisticated value investing strategy. They enhanced their factor by insights that are well documented in the literature or in the common knowledge of the practitioners. They used a composite of value metrics, apply some basic risk management and they limit the companies only to large/mid-caps. First adjustment is that they augment book-to-market ratio with three alternative value signals: EBITDA/EV, CF/P (Cash Flow-to-Price) and NPY (Net Payout Yield). Net Payout Yield corresponds to dividend yield, plus share buybacks, minus share issuance. They computed all the value metrics by using the most recent price. The composite value score was created by first normalizing each metric cross-sectionally using standard robust z-scores, capped at +3 and -3, and then normalizing these scores. Figure 2 presents the cumulative return of the enhanced value factor. It performed clearly better than the traditional value factor even though it excluded small caps altogether.

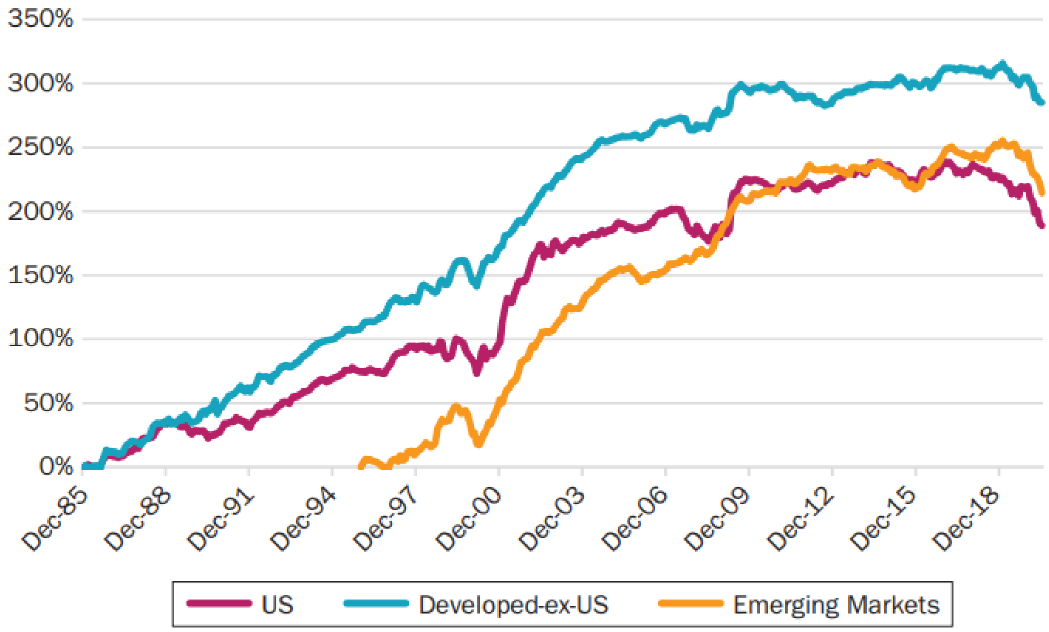

Figure 2 Cumulative return of enhanced value factor (Blitz and Hanauer 2021)

Dhatt et al. (1999) reported the results of performance comparisons between value portfolios which were formed from both individual valuation ratios (E/P, B/P and S/P ratios), and from their combinations. For the period between 1979-1997, the composite value portfolio achieved the best results based on both absolute and risk-adjusted returns amid all the portfolios.

Pätäri et al. (2016) study found that different value strategies performance is dependent on the market conditions. They decomposed their value portfolio performance on bull and bear market periods between 1993-2013 in the Finnish stock market. Bull market is defined as 25% gain (loss) in the value of the market portfolio from the previous low (peak). They got an aggregate bull market period that includes 149 monthly returns and consisted of six discrete bullish periods. They got an aggregate bear market period that included 55 monthly returns and consisted of five discrete bearish periods.

Interestingly they found that the added value generated by value investing strategies in the Finnish market has been totally during the bearish periods. Strikingly during the bullish periods, none of the active portfolios outperformed the market portfolio. In contrast, during the bearish periods majority of active portfolios have been incurred to far less losses than the market portfolio, thus having significantly outperformed the latter. They argue that this phenomenon is largely explained by the structure of Finnish stock market, because few large-cap companies dominate the development of the Finnish stock market indices. In comparison, the value portfolios were all broadly diversified and equally weighted once a year every reformation date, and therefore they couldn't benefit from the appreciation of the dominant large caps the same way as the market portfolio.

Interesting observation from the study is that the portfolio based on the bottom tercile B/P (in other words, expensive) performed clearly best among the B/P terciles when the market conditions were bullish, whereas the B/P top tercile portfolio generated lowest returns. During the bear market the opposite was true, the bottom B/P tercile portfolio was extremely sensitive to the stock market declines. It had lost 44.71% p.a. of its value during the bearish market conditions. The massive drop in the asset value ate all its gains earned during the bull market period against the top B/P tercile portfolio. In conclusion, the low B/P multiple seems to be extremely sensitive to volatile stock markets.

2.4 Value investing strategies

Investors who are following value investing strategies in the stock market buy stocks that have low prices relative to their earnings, dividends, book assets, or other measures of fundamental value. For example, buying a company with low P/E-ratio compared to the comparable companies or to high growth prospects. Value investing has been a popular strategy among the practitioners and many of the most well-known practitioners, like Warren Buffet and Benjamin Graham for example, have advocated for the value investing approach. Practitioners believe that they can buy companies below their intrinsic value by following value investing strategies. The popularity of the strategy has been supported by academic evidence for the higher returns compared to the growth strategies. However, during the 2010's the traditional value investing strategies have performed poorly compared to growth strategies.

Choosing the right multiple is not an easy task and the academic findings are mixed. Gray and Vogel (2012) analyzed different valuation measures over a 40-year period between 1971 and 2010 in US stock market. Their basic research objective was to determine which valuation metrics has historically performed the best. They argue that practitioners rely on a variety of valuation measures, including price-to-earnings ratio (P/E) and the relationship between total enterprise value and earnings before interest, taxes, depreciation, and amortization (EV/EBITDA). Instead, academic research has traditionally relied on the book-to-market ratio (B/M) and the more recent gross-profits measure (GP). Gray and Vogel (2012) found economically and statistically significant differences in the performance of different valuation metrics. In their study they considered: Earnings-to-market capitalization (E/M), earnings before interest, taxes, depreciation, and amortization-to-enterprise value (EBITDA/EV), free cash flow-to-enterprise value (FCF/EV), gross profits-to-enterprise value (GP/EV), book-to-market (B/M) and forward earnings estimates-to-market capitalization (FE/M).

They found that during the analyzed period EBITDA/EV was the best valuation metric to use as an investment strategy. They found that an annually rebalanced equal-weight portfolio of high EBITDA/EV stock earned 17.66% a year, with a 2.91% annual three-factor alpha. Instead, cheap E/M stocks earned 15.23% a year, but the alpha faded away after controlling for the market size. The cheap B/M stocks told a similar story to the E/M stocks, they earned 15.23% a year, but showed no evidence of alpha after controlling for market, size, and value exposures. Forward-looking FE/M performed poorly. (Gray and Vogel 2012)

Enterprise value-based (EV) multiples have been studied less compared to the market capitalization-based multiples. But the research has been increasing in popularity during the more recent years. One reason for the increasing popularity is that the enterprise value-based multiples can be compared more easily across firms with diverging leverage because enterprise value also considers the firm's financial situation by adding net debt to the market capitalization. The use of EV-based multiples as the basis of value investing strategy is also justified by the fact that in case of acquisition, acquirer must take the responsibility of the acquisition target's debt. Correspondingly, investor should not ignore the debt either because he is actually buying a piece of a real company when he invests in its stock. The most used EV-based multiples in the value investing literature are EBITDA/EV, EBIT/EV (earnings before interest and taxes-to-enterprise value) and S/EV(sales-to-enterprise value). In addition, GP/EV (gross profit-to-enterprise value), FCF/EV (free cash flow-to-enterprise values) and CF/EV (operating cash flow-to-enterprise value) have been studied. (Pätäri and Leivo 2017)

Gray and Vogel (2012) found that EBITDA/EV was best performing between EBITDA/EV, FCF/EV, E/P, B/P and GP/EV. They formed 25 quintile portfolios and the EBITDA/EV top-quintile portfolio was the best performing. Leivo et al. (2009) found also that the top quintile EBITDA/EV portfolio performed best between (EBITDA/EV, E/P, B/P and S/P). Pätäri et al. (2016) reported that EBIT/EV documented the best performance between (EBIT/EV, E/P, B/P and S/P). Davydov et al. (2016) also found evidence for the relative superior performance of EBIT/EV in the Finnish stock market between 1991 and 2013. They compared EBIT/EV, E/P, CF/P and B/P with forming top 30% equally weighted portfolios.

Schreiner (2009) found that equity value multiples explain market values better than corresponding entity multiples. For example, P/EBIT explains better market values than EV/EBIT. This is contrary to the practitioners' beliefs and to what theory suggests. Theory suggests entity values would work better because they are less affected by different capital structures among comparable firms. Schreiner (2009) found that in 15 out of 16 valuation multiples equity-based multiples had lower median valuation error and he concluded that equity value multiples outperform entity value multiples in terms of valuation accuracy. He argues that the underlying reason for this conclusion is that noise in the estimation procedure of the enterprise value distorts the reliability of entity value multiples. However, here the important thing to consider is the distinction between valuation accuracy and predictive power. His research method was value relevance of the valuation multiples which is different from the earlier presented studies which use portfolio method and study how multiples predict returns. He defined value relevance as: *"the association between accounting information and market variables, particularly over a long horizon, indicates only that the accounting information in question is correlated with the information used by market participants."*. In addition, he operationalized the "goodness of fit" of a valuation method. That is, "*If value predictions based on a certain valuation model explain market values reasonably well, the value relevance of the model's variables is thought to be relatively high. In other words, value relevance depends on the convergence of market value and intrinsic value, as estimated by the valuation model"*. His main measure of performance was median valuation error.

Pätäri et al. (2016) found that in the Finnish stock market between EBIT/EV, P/B, P/S and P/S over the 1996–2013 sample period EBIT/EV had highest geometric return 14.35% of the all the portfolios based on individual valuation multiples. Also, EBIT/EV portfolio's SKASR was the highest. SKASR refers to the skewness and kurtosis adjusted Sharpe ratio. By contrast its volatility was amongst the lowest. They found that B/P also had good discriminatory power in a way that returns were monotonically decreasing from top tercile to the bottom tercile, while the reverse held for the risk measures (volatility and SKAD, SKAD is skewness and kurtosis adjusted volatility). E/P and S/P didn't work so well as individual multiples, which is consistent with earlier research obtained from the Finnish stock market. E/P generated highest returns for the middle tercile, and S/P for the lowest tercile, while having weak discriminatory power on separating the best- and worst- performing stock of the future. Earlier research had documented evidence in the support of S/P multiple in different markets, but this was not seen in the Pätäri et al. (2016) study. Amongst the multiples, EBIT/EV had highest discriminatory power, with corresponding value premium of 7.73%.

2.5 Combining value and momentum

Momentum is the rate of acceleration of a security's price. In other words: the speed at which the price is changing. Momentum strategy seeks to capitalize on momentum to enter a trend as the trend is expected to continue. Many financial institutions have funds that are exploiting the momentum effect. Alongside with value, momentum anomaly has been found to be the most persistent in the stock markets.

Asness (1997) discovered in an early paper negative correlation between value and momentum. Among the loser stocks value was the strongest while among the growth stocks momentum was the strongest. A negative correlation between two high-yielding anomalies could present an opportunity to earn abnormally high returns at relatively low portfolio risk. Asness (1997) used in the value strategies industry weighted B/P and D/P as the valuation multiples. Asness et. al (2013) investigated the value and momentum strategies across eight different asset classes and markets from 1970s to the 2010s. They also found negative correlations between value and momentum strategies. Value and momentum strategies yielded abnormal returns in all the markets, except momentum was not a successful strategy in Japan. They also studied combined strategies. Their results show that a combination of value and momentum strategies improved the overall performance in terms of Sharpe ratio and performed exceptionally well. They found that a simple combination of the two strategies was closer to the efficient frontier than either of the strategies alone and exhibits less volatility across the different markets and over time. Their sample was restricted to roughly 20% biggest companies in the markets. As the value signal they used traditional B/P multiple with 6-month lag and as the momentum signal 12-month momentum with 1-month lag. They found that using non-lagged B/P would not have impacted the results. Cakici and Tan (2014) also found that in almost all developed countries there exists the negative correlation between value and momentum within the country as well as across countries.

Leivo (2012) studied value and momentum in the Finnish stock market between 1993 and 2009. He used a wider set of multiples: E/P, EBITDA/EV, CF/P, D/P, B/P and S/P. As the momentum signal, he used six-month momentum. Leivo observed that taking account of price momentum beside valuation criteria improves the performance of most of the best value-only portfolios. He also discovered that the inclusion of momentum increases the asymmetry of the return distribution in unfavorable way. He concluded that incorporating momentum benefits most the value portfolios which are formed on composite criteria. Leivo also found that incorporating momentum alongside with momentum improves the performance only during the bull market periods but deteriorates the returns during the bear market periods.

According to Grobys and Huhta-Halkola (2019) combining value strategies with momentum strategies increased Sharpe ratios and offers investors significant diversification benefits in the Nordic stock markets. They found that all the investigated combination portfolios improved the Sharpe ratios compared to the pure-play value strategies. According to their results the ranking scheme method to construct combination portfolios was superior compared to simple 50/50 allocation strategy. The ranking scheme creates an average ranking between momentum and value signals. Compared to the pure-play value strategies, the ranking scheme combination portfolios returned higher raw returns and Sharpe ratios, but the 50/50 portfolios exhibited lower raw returns but higher Sharpe ratios due the lowered volatility. The studies done on combining the value and momentum strategies have found that in general combination portfolios do improve the portfolio performance compared to the pure-play value strategies. However, it is good note that the bulk of the studies are done based on B/P ratio.

3 VALUATION IN THE TECHNOLOGY SECTOR

3.1 Investing in the technology sector

Technology sector often exhibits special qualities which makes it hard to apply traditional valuation multiples, especially with the younger and fast-growing companies. Because their main value drivers are intangible assets and R&D investments, they are often "punished" in the traditional and most used valuation multiples, such as P/E, P/B or EV/EBIT. This is because R&D expenses are treated more as expenses and not as investments which is often their true nature. R&D investments are commonly either expensed directly in the income statement or amortized very aggressively compared to the tangible assets. This in part, has led to investors prioritizing revenue growth or non-accounting metrics such as user growth. Though, the use of these metrics can be also rational if the earnings are negative. The academic research focusing especially on the technology sector is quite scarce.

Schreiner (2009) found that knowledge-related multiples outperform traditional multiples in science-based industries in Europe and in the US. Knowledge-based multiples that he used were *P/(EBIT+R&D), P/(EBIT+AIA), P/(EBIT+KC), P/(E+R&D), P/(E+AIA) and P/(E+KC). AIA* = Amortization of Intangible Assets, *KC = (AIA + R&D)*. His method of comparing the multiples was value relevancy. Milano et al. (2016) found that in the US technology sector R&D expenses play important part in the value generation. They also found evidence for ROE and Sales GAGR to be important return factors.

Scheiner (2009) found that in the US Technology sector, which was more relevant sector in 2007 compared to Europe's technology sector, best performing multiples were knowledge-based multiples. Four best performing trailing multiples were *P/(EBIT+KC)*, *P/(E+KC)*, *P/(E+AIA)* and *P/(EBIT+AIA)*. Also, in the US Technology sector forward-looking multiples performed better than trailing multiples, and the best performing multiples were *P/E2* (2 years forward-looking), *P/E1, P/EBIT2, P/(EBIT+KC)*. Scheiner could not include knowledge-based multiples in his forward-looking multiples because there were no analyst forecasts for these multiples available.

Discounted-cash-flow models suggest that companies with higher growth potential and lower discount rates (required rate of return) should have higher valuation multiples relative to companies with contrary characteristics. To modify the classic P/E ratio to account for the higher growth potential, investors have standardized the P/E ratio by company's growth rate, the metric commonly known as PEG ratio. Schatzberg and Vora (2009) discovered PEG effect in equity returns. They found that growth selling at a discount measured by PEG outperformed more expensive alternative investments. However, PEG ratios can work only if the earnings-component relevant as well.

Trueman at al. (2000) studied the high flying internet stocks. They discovered that was insignificant assocition between the reported net income and market value. They found that gross profits are positively associated with the market value. They also found that metrics such as pageviews alongside with net income components retain a significant association with the market prices. However, it is good to note that this study was conducted almost at time of the all time high market prices during the tecno bubble. Rajgopal et al. (2003) also found evidence of association between web page visits and market prices in the e-commerce stocks.

Valuation methods are based on the accounting methods and the accounting methods have been a subject of criticism often for that they do not reflect the company's actual performance in the real-life. This criticism has been brought into the table especially in the case of fast-growing technology companies which often are not profitable, or their profit margins are significantly lower than some other sectors with more mature companies. According to Chan et al. (2001) the market is too pessimistic about the R&D-intensive technology companies which profit margins are depressed by heavy R&D-spending. They discovered that companies with high R&D expense-to-equity market value ratio earn large excess returns. They also observed that a similar relation exists between advertising and stock returns.

Since the recent financial crisis in 2010s the performance of high book to market value companies have outperformed the value stocks by a wide margin. This is contrary to the value anomaly that is considered to exist in the stock market. The intangible assets explain bigger portion of the book value, but still most of the research & development are expensed on the income statement and not capitalized into the balance sheet. Lev and Srivastava (2019) studied the underperformance of the traditional value investing strategy. They created an adjusted value strategy where they capitalized the research & development expenses and part of the sales, marketing and administrative expenses and amortized these from the balance sheet. Then they selected these value stocks based on the new market-to-book value rankings. Roughly 40-60% of the companies changed in the portfolios after these adjustments. As can be seen from Figure 3, the adjusted value strategy (blue bars) outperformed by wide margin the traditional value investing strategy (red bars). From Figure 2 we can see that in the 1980s the adjusted value strategy clearly started outperforming until 2018 almost every year. Lev and Srivastava argue that this reflects the fact that the value creation is based on the intangible assets more than it used to be.

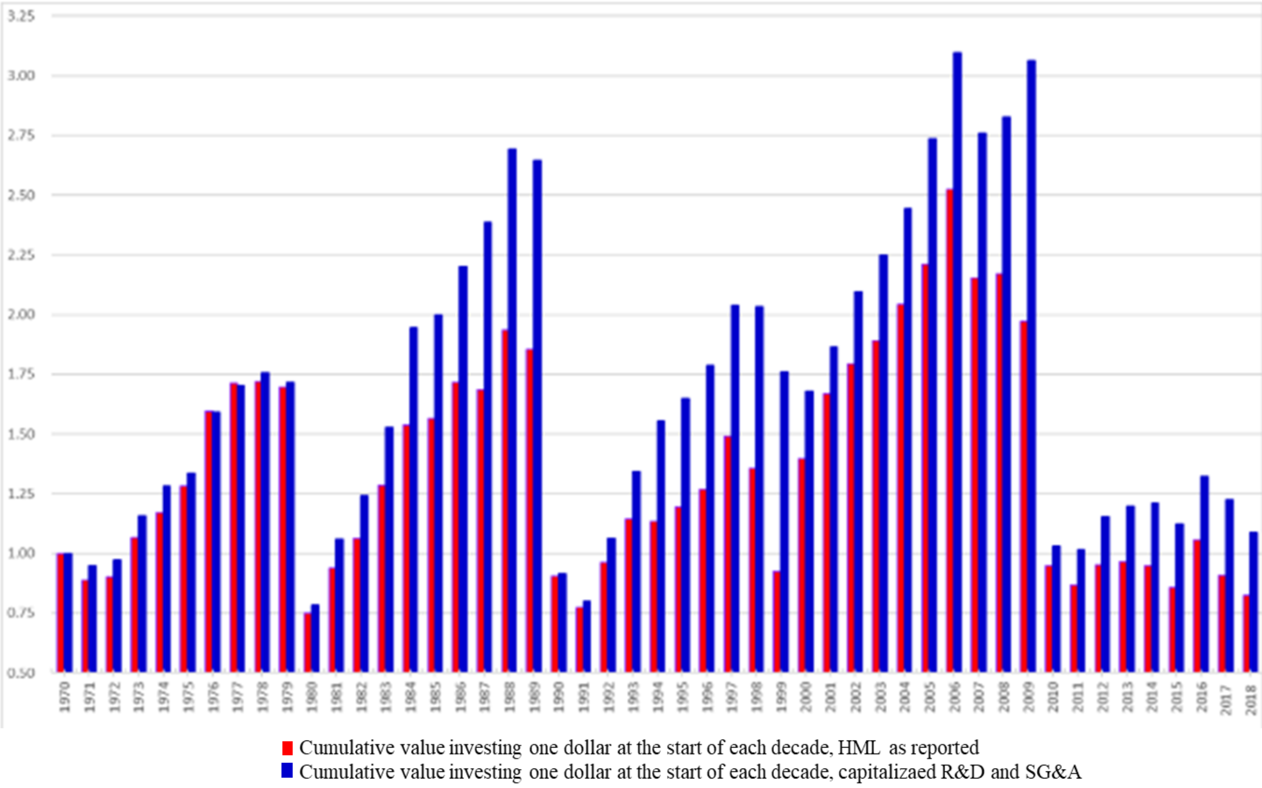

Figure 3 The cumulative returns of Adjusted Value strategy vs Value strategy (Lev and Srivastava 2019).

Up until late 1980s companies invested mainly in tangible (physical) assets, for example property, plant, equipment, structures, airplanes, which are capitalized by the accounting rules and therefore fully reflected in the firm's balance sheet. Since then, the investments in intangible assets have increased rapidly and nowadays firms invest considerably more in them than in tangible assets as can be seen from Figure 4. This trend is very unlikely to change in the future. (Lev and Srivastava 2019)

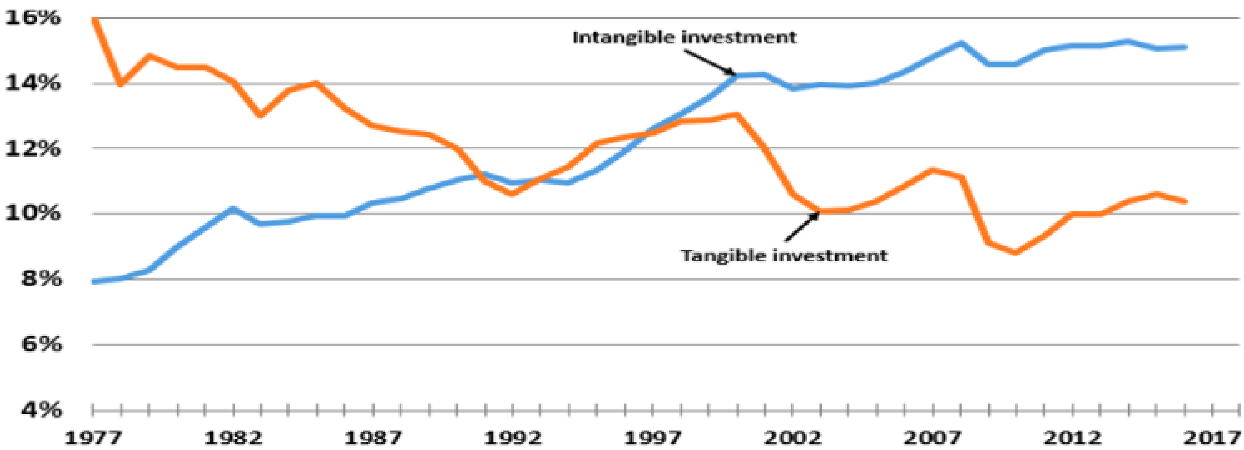

Figure 4 Investment rates in tangible vs intangible assets in US private industries 1977-2017 (Lev and Srivastava 2019)

IAS 38 defines the criteria for recognizing and measuring intangible assets and requires disclosure about them. IAS 38 defines intangible asset as an identifiable non-monetary asset without physical substance. This kind of asset is identifiable when it is separable, or when it arises from contractual or other legal rights. Separable assets can be sold, transferred, licensed, etc. Instances of intangible assets include computer software, licenses, trademarks, patents, brands, copyrights, and import quotas. Goodwill which is acquired in business transaction is accounted for in accordance with IFRS 3 and not within IAS 38. Internally generated goodwill is inside the scope of IAS 38, but it is not recognized as an asset because it is not an identifiable resource. IAS 38 requires for capitalizing R&D expenses that: it is probable that there will be future economic benefits from the assets; and the cost of the asset can be reliably measured. Because the cost of generating an intangible asset internally is often difficult to distinguish from the cost of maintaining or enhancing the company's operations or goodwill internally developed brands, publishing titles, customer lists and similar lists are not recognized as intangible assets. (IFRS.org)

Rajgopal et al. (2003) showed that network advantages create an important intangible asset that goes unrecognized in the financial statements. They studied a sample of e-commerce firms. Network advantage is defined as follows, when a benefit from being a part of a network increases with the larger number of people or companies connected to it. They discovered that for the e-commerce firms the network effects created by web site traffic produce an important intangible asset which is valued by the stock market above accounting measures such as current earnings and book value of equity. They studied the value relevancy.

3.2 Valuation of loss-making growth companies

Large portion of firms, especially high growth technology firms, report losses. The big investments in Sales and R&D are often front-loaded and expensed directly as expenses. Valuation of loss-making firms is not possible with earnings multiples, especially with P/E-ratio. This is one of the reasons why for example EV/Sales-ratio has become so popular in the technology sector. The current importance of loss-reporting firms creates the need for valuation tools which can be applied to loss-making companies.

Earlier research suggests that loss-making firms are valued based on their abandonment/adaptation option values, unlike the profit-making firms that are valued as going concerns. Hayn (1995) concludes that the shareholders of loss-making firms can always exercise their abandonment options and liquidate their firms, so they don't need to suffer from prolonged or indefinite losses. Which implies that losses are probably temporary and may not be informative about firm value. Hayn (1995) finds out that earnings-return association is significant and highly positive for profit-making companies, but insignificant for loss-making firms. Shareholders of loss-making firms have a put option to sell their shares at price which corresponds to the market value of net assets. This finding suggests that investors do not evaluate loss-making companies on the basis of reported earnings, but rather on book value of net assets (the abandonment value).

Another branch of research focuses on the accounting for loss-making firms. Research & development expenses are one of the primary reasons for the growing number of loss-making companies. Expensing the R&D expenses in the income statement can create conservative bias into accounting numbers and this leads to many companies, which are investing heavily to R&D to increase future cash flows, reporting losses even though they are not in financial distress. (Ciftci and Darrough 2015) Darrough and Ye (2007) state that many companies which report losses are not the stereotypical distressed company that may face bankruptcy or liquidation, but rather they report losses because of the conservative treatment of R&D expenses. They argue that valuation methods based on abandonment/adaption option value do not apply to many R&D-intensive loss-making companies.

Darrough and Ye (2007) focused in their research on loss-making firms that are likely to stay in the business for a long time. These firms are likely to survive and receive high market valuation because their current accounting earnings and book values do not fully capture their future earnings potential. They tested four value drivers for this type of firms to solve the puzzling negative relation between earnings and market value found in the prior research. They searched scenarios in which current reported losses are expected to produce a reversal in profits in the future. They focused on four potential value drivers: 1) nonrecurring charges, 2) research & development 3) growth strategy and 4) sustainability. These four value drivers are variations of the same theme. Current earnings are depressed for higher future earnings. Thus, large losses now are forerunners of positive future earnings. If the market is anticipating this, it rewards the firm with high valuation.

Darrough and Ye (2007) found out that there were two major factors that were responsible for the negative relation between the market values and their earnings. The first one was the requirement to expense R&D. They found that loss firms are on average more R&D-intensive (R&D in relation to revenue) than profit firms, and firms with larger losses are even more R&D-intensive. Their analysis suggests that larger number of loss firms is closely linked with the increase in the number of small companies that engage in risky R&D project that do not produce current profits. Expensing R&D creates substantial losses for these firms, even though their R&D investments are valued by the market. Therefore, to certain degree, the negative relation is an artifact of conservative R&D accounting. This emphasizes the problem of R&D expensing in the economy where R&D activities have become one of the main value drivers. The second driver for the negative driver was sustainability. Darrough and Ye (2007) defined sustainability as an ability to obtain external financing through stock offering and debt issuance or generate cash. They argue that loss firms that can obtain external financing have hidden assets, like brand names or other intangibles, that are valued by the market but not by the accounting system. Interestingly, they also found that sales growth was not a major factor and contrary to the assumption that loss-making firms are growth companies, they, on average had lower growth in sales than profit-making firms (2.1% vs. 13.4%). Sales growth had statistically significant, but small effect.

Ciftci and Darrough (2015) studied how valuation differs between loss- and profit-making firms that invest in intangibles and how expensing vs. recognizing intangibles affects valuation. They found that book value is more prominent in valuation of loss-making companies than profit-making companies with low R&D intensity than with high R&D intensity, which supports the abandonment/adaptation option argument. Jiang and Stark (2013) found similarly that book value is a less important determinant of equity value for firms with high R&D intensity. Jiang and Stark (2013) also argue that book value is less important determinant of equity value for dividend-paying companies, relatively to non-dividend paying firms in the UK stock market. A bit surprisingly Ciftci and Darrough (2015) also found that book value has more prominence for loss-making companies than profit-making firms in all groups of recognized intangibles as the abandonment/adaptation option value predicts, thus suggesting that recognition of intangible assets eliminates the conservative bias in accounting statements. Their findings suggests that capitalization of R&D expenditures and probably other intangible assets could improve the value relevance of financial information. In other words, capitalization of R&D expenses might reduce the conservative bias in accounting numbers, which would lead to fewer R&D intensive firms reporting losses. Can be concluded, according to prior research that it is important to separate loss-making firms that are in financial distress and loss-making firms that are investing heavily to the future and because of this are reporting losses.

4 DATA AND METHODOLOGY

4.1 Data and definitions

The sample consists of public companies in the technology sector listed in the Nordic stock exchanges (Sweden, Norway, Finland and Denmark, excluding Iceland) during the period between 2006 and 2021. The sample contains companies from the main lists and from the First North lists, in addition some technology intensive companies from Finland are included in the sample. Only Finnish companies are considered because the author knows them well. Technology sector also includes telecommunication stocks. The included companies[1] are technology intensive and the main driver of their fundamental business success could be characterized in their technological innovations. The total returns and the financial variables are obtained from the Refinitiv Eikon database. The sample period is from 31st March 2006 until 1st April 2021. The data span should be sufficient to study these investment strategies and it includes bear markets of the Financial crisis, Euro crisis and the Covid-19 crisis which makes it possible to study the performance of the strategies during the bull and bear markets. To avoid the survivorship bias, the sample also includes the stocks of the firms that went bankrupt or were delisted during the time period. The list of the delisted companies is collected from Bloomberg (2021) terminal and then these companies were picked manually from the Refinitiv Eikon database.

Table 2 Number of companies in the samples

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Main Sample	113	122	126	112	121	123	109	117	115	129	140	164	196	226	256
Momentum Sample	104	115	112	107	116	116	100	108	111	110	124	143	160	204	242
Fo_S EBIT	70	73	81	68	81	84	69	79	72	67	76	102	124	132	142
Fo_S EBITDA	70	72	81	68	76	83	68	78	71	64	77	101	124	133	141
Fo_S E(Adj.)	75	81	88	82	90	91	89	89	87	87	83	108	129	151	158
Fo_S Sales	76	83	93	88	93	94	92	91	88	88	84	109	131	153	160

Sample is divided into three different sub-samples: 1) main sample, 2) momentum sample, and 3) forward-looking sample (Fo_s). Forward-looking sample is then further divided into four sub-samples based on whether the company has the forward-looking estimate for the financial attribute in question: 1) EBIT, 2) EBITDA, 3) Net Income, and 4) Net Sales. Motivation for this further sub segmenting is that the sample sizes for the

[1] Detection technology, Optomed, Revenio, Talenom

forward-looking samples would have become small and the most interesting question to examine within this sample is whether value strategies based on forward-looking analyst estimates beat the strategies based on historical accounting numbers. For example, whether 12F_EBIT/EV (12F = Next Twelve Months) beats LTM_EBIT/EV (LTM = Last Twelve Months). As can be seen in Table 2, the total number of companies per year for the main sample ranges from 109 to 256, for the momentum sample from 100 to 242 and for the forward-looking samples from 64 to 160. The number of companies in the sample stays relatively stable from 2006 to 2015 and then from 2015 to 2020 we can see that multiple new companies spawn each year. In the main sample the companies increase approximately by 30 every year. Typically, number of initial public offerings increase during the long bull markets, especially in the hot industries like technology sector.

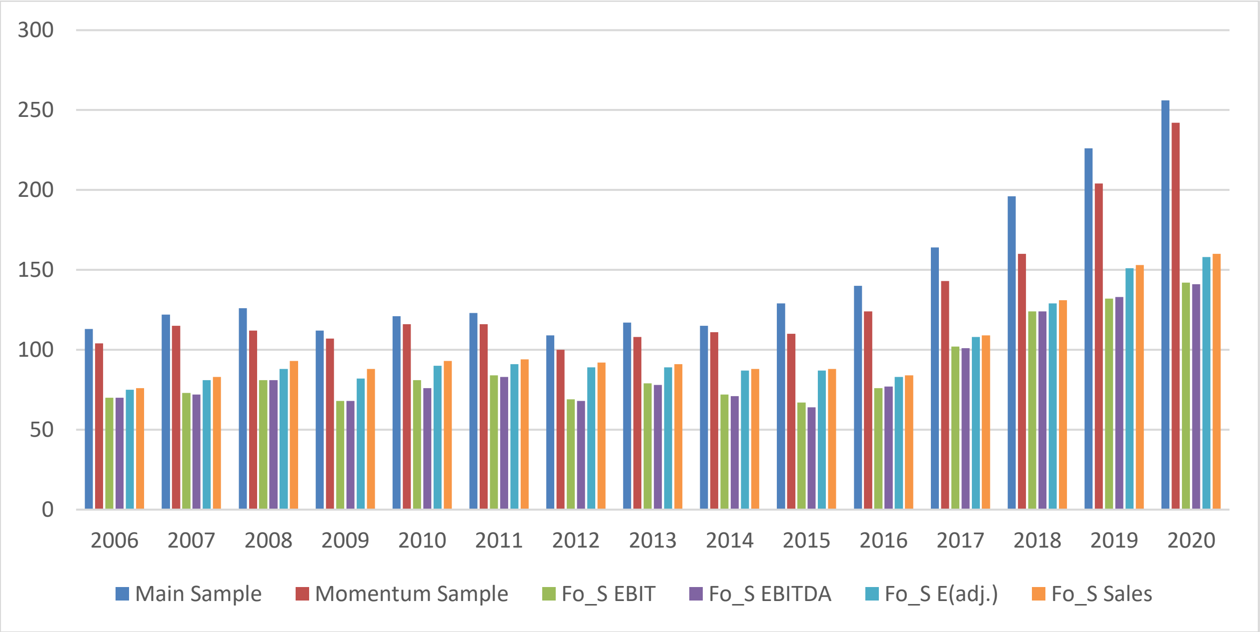

Figure 5 Number of companies in the samples

Technology sector is compared to the overall Nordic market. The index used for the overall Nordic market is FTSE Nordic all cap Growth Index which includes dividends. This benchmark index is the best available option because it includes all capitalization classes. All the markets have different currencies (Finland: Euro, Denmark: Danish kronor: Sweden: Swedish kronor, Norway: Norwegian kronor), and they are all converted to euros automatically in Refinitiv Eikon. 12-month Euribor is used as the risk-free rate.

The returns are calculated using daily Total Return Indexes (TRI) which adjusts for dividends, splits, and capitalization issues accordingly. If a firm has had two or more stock series listed, only the one with higher liquidity is included in the sample selection. If the financial year of the company does not equal a calendar year, it will be excluded from that year's sample. This avoids the problem that might arise from the look-ahead bias.

Table 3 reports the summary statistics of the different samples. Small Cap stocks heavily dominate the technology sector, in the main sample and momentum sample they account for 72.3-73.8% of the firms. In the forward-looking samples they account for 59.1-63.7% of the firms. Respectively Mid-Caps account for 17.4-18.1% and 23.7-26.2% and Large Caps for 8.8%-9.6% and 12.6-14.7%. Median market capitalization ranges from 53.3 to 110.6 million euros. Swedish companies have proportionally high weight in all the samples, ranging from 51.6-59.2%. Finnish firms weight ranges from 19.6% to 26.6%, Norwegian firms from 14.8% to 18.1% and Danish firms from 4.5% to 6.3%. We can observe from the data that in the technology sector Finnish and Norwegian companies have proportionally higher analyst coverage compared to Swedish and Danish firms. Interestingly compound annual growth rates for the samples drop the less stocks are included in the sample, ranging from 12.5% to 15.5%. This is linked to the fact that Small Cap stocks outperformed the larger ones during the observation period. All though, all samples still outperformed the FTSE Nordic Small Cap index (CAGR 10.2%). The Nordic technology sector could be fruitful for value investing strategies as per Fama and French (2012) and Cakici and Tan (2014) reported, the value premium was stronger in the small-caps than in the larger-caps.

Table 3 Sample summary statistics

Sample	Small Caps (%)*	Mid Caps (%)*	Large Caps (%)*	Market Cap mean*	Market Cap median *	Swedish Firms (%)*	Finnish Firms (%)*	Norwegian Firms (%)*	Danish Firms (%)*	Company years in total	Market CAGR	Market CAGR Pre-Covid**	Number of unique Firms
Main Sample	73.8%	17.4%	8.8%	1074.7	53.3	59.2%	19.6%	14.8%	6.3%	2169	15.5%	11.9%	332
Momentum Sample	72.3%	18.1%	9.6%	1167.4	59.7	59.1%	19.9%	14.9%	6.1%	1972	14.7%	11.0%	315
Fo_S EBIT	59.2%	26.2%	14.5%	1735.1	110.6	52.1%	26.2%	17.0%	4.7%	1320	12.5%	8.9%	229
Fo_S EBITDA/EV	59.1%	26.2%	14.7%	1755.3	109.8	51.6%	26.6%	17.0%	4.8%	1307	13.1%	9.5%	232
Fo_S E(adj.)/EV	63.4%	23.8%	12.8%	1536.6	95.9	52.3%	24.9%	18.1%	4.6%	1488	13.2%	9.6%	233
Fo_S Sales/EV	63.7%	23.7%	12.6%	1503.2	95.4	52.9%	24.6%	18.0%	4.5%	1523	13.3%	9.8%	234

*Averages of yearly averages. For example, in the Main Sample through the investigation period on average 73.8% of yearly averages are Small Caps
**Pre-Covid time-period= Until 31.1.2020.

4.2 Portfolio construction

4.2.1 Main portfolios

The main study method is portfolio method. The research methodology follows closely Davydov et al. (2016) methodology. All the portfolios are long-only portfolios. This is justified by the fact that it is not even possible to take short positions on large part of the Nordic technology sector stocks. The portfolios are formed based on the valuation ratios. Portfolio method has been previously widely used in the value investing research. Portfolios are formed once every year. The portfolios are formed on the first day of April, when all the firms that follow regular calendar year reporting have reported their financial statements. If the April 1st is either a Saturday or Sunday, then the portfolio will be formed on Friday. Thus, the portfolio construction is based on the accounting data as per the end of the previous year and for stock prices in the beginning of April. Closing stock prices are used. For example, EBIT/EV calculation is following:

$$EBIT/EV_t = \frac{EBIT_{t-1}}{EV_t},$$

where $EBIT_{t-1}$ is EBIT in the previous calendar year, EV_t is enterprise value on 1st of April. All portfolios are equally weighted, and the holding period is 1 year. Value-weighted portfolios are not investigated due to few very large stocks causing massive bias. The requirements for each stock to be included in the sample for each year, it must have in Refinitiv Eikon database 1) EV/EBIT for at least one year during the whole sample period 2) All the financial variables defined in Table 4 for the preceding year 3) The average weekly trading volume must be higher than 5000 euros 4) The preceding financial year must end on 31st of December 5) The stock must be trading on the portfolio formation date. In addition, in the momentum sample 6a) the stock must have the total return for the past 12 months and for the forward-looking samples 6b) the stock must have estimates for the financial variables defined in Table 7. All stocks with incomplete data are excluded from the portfolio formation for the year. If the company has gone bankrupt during the holding period, the return for that stock is -100%. If the stock is delisted without going to bankrupt, it is assumed that the stock is sold on the last trading day and the corresponding amount is invested in the risk-free rate until the end of the holding period.

For each valuation metric three different strategies are implemented. Portfolios are created from the top 30%, top 20% and top 20 stocks in each ranking method. For example, top 30% E/P-ratio portfolio includes top 30% of the stocks with the highest E/P-ratio and top 20 portfolio includes 20 stocks with the highest E/P-ratio. For each year, if the top 30% or top 20% portfolio would amount for less than 20 stocks, then the top 20 stocks are selected.

Table 4 presents all the implemented valuation multiples. For most of the multiples, EV-based and equity-based multiples are provided. In the earlier studies about valuation multiples with the portfolio method the multiples that have been used, have been mainly taken as a status quo from the earlier studies or from the finance industry. For example, no studies were found that compare E/P and E/EV. Only studies with S/EV and S/P have been found which use the same value driver (sales) but even these two multiples could not be found simultaneously in the studies. This is puzzling, considering how limited and mixed our understanding of the stock markets valuation process still is. Therefore, many multiples are studied that have not been studied earlier. For example, EBIT/P, EBITDA/P, E/EV, B/EV. Simple adjustment is also made to study valuation multiples that reflect better the firm’s fundamental operational performance. The adjustment is computed by subtracting operating income from EBIT. This adjustment should eliminate most of the non-operating profits and costs which do not reflect the firm’s true operational performance and are most of the time one-time events. OPE+D&A is effectively equal to the adjusted EBITDA. All the explanations for the financial variables and the calculation method can be seen in Table 5. Multiples which incorporate research & development costs, or which are based on gross profit are excluded because the gross profit measures in the samples were too low-quality data in the Refinitiv Eikon database and the sample size including multiples with research & development costs would have become too small.

Table 4 Valuation multiples in the main sample

Implemented multiple	Consists of
OPE/EV	Operating income / Enterprise value
EBITDA/EV	Earnings before Interest, Taxes, Amortization & Depreciation/ Enterprise value
(OPE+D&A)/EV	Operating income + Depreciation / Enterprise value
S/P	Net Sales/ Market Capitalization
EBIT/P	Earnings before Interest and Taxes/ Market Capitalization
EBITDA/P	Earnings before Interest, Taxes, Amortization & Depreciation/ Market Capitalization
CF/P	Operating Cash Flow/ Market Capitalization
(OPE+D&A)/P	Operating income + Amortization & Depreciation / Market Capitalization
OPE/P	Operating income/ Market Capitalization
S/EV	Net Sales/ Enterprise value
EBIT/EV	Earnings before Interest and Taxes// Enterprise value
E/P	Net income/ Market Capitalization
E(Adj.)/P	Adjusted Net income/ Market Capitalization
CF/EV	Operating Cash Flow/ Enterprise value
D/P	Dividend yield
B/P	Book Value/ Market Capitalization
E(Adj)/EV	Adjusted Net income/ Enterprise value
B/EV	Book Value/ Enterprise value

Table 5 Explanations for the financial variables

Refinitiv refers to the Refinitiv Eikon database.

Abbreviation	Name	Calculation method
OPE	Operating income	Directly from Refinitiv
EBITDA	Earnings before interest, taxes, depreciation & amortization	Directly from Refinitiv
OPE+D&A	Operating income + depreciation & amortization	OPE + D&A
S	Net Sales	Directly from Refinitiv
EBIT	Earnings before interest and taxes	Directly from Refinitiv
CF	Operating cash flow	Directly from Refinitiv
E	Net Income available to common	Directly from Refinitiv
D	Dividend yield	Directly from Refinitiv
E(Adj)	Adjusted Net Income	E + Adj.
B	Book Value	#Shares * BPS
D&A	Depreciation & Amortization	EBITDA – EBIT
P	Market Capitalization	Directly from Refinitiv
EV	Enterprise Value	P + Net Debt
#Shares	Common shares outstanding	Directly from Refinitiv
BPS	Book Value per Share	Directly from Refinitiv
Adj.	Adjustment for the actual operational performance	Operating Income - EBIT
Net Debt	Net Debt	Directly from Refinitiv

4.2.2 Momentum portfolios

Along with value, price momentum is the most robust capital market anomaly. It has been profitable on its own and it tends to perform well when value underperforms which can provide significant diversification benefits for the investors. (Novy-Marx 2013 (2)). Often momentum strategies are implemented as long-short strategies which is long winners, and short losers. In this study momentum portfolios are also long-only portfolios because of the shorting restrictions involved within the Nordic technology sector.

Momentum portfolios are also 1-year buy and hold strategies. Often in the momentum literature, portfolios are rebalanced more often but in this study 1-year buy and hold strategy is chosen. Two different combination strategies between value and momentum are implemented: simple 50/50 allocation between momentum and value and a ranking scheme. These two methods were used also by Grobys and Huhta-Halkola (2019). In the 50/50 portfolios half of the portfolio is invested in value and the other half in the momentum portfolio. In the ranking scheme stocks are ranked based on value and momentum scores and then the average of the two scores is calculated. The ranking is linear ranking where one place upward in the ranking equals one more relative point. Six different momentum multiples are tested before constructing the combination portfolios. The tested momentum signals are the most common in the momentum literature: 12-month, 6-month and 3-month momentum and the 1-month lagging multiples for these multiples (for the 3-month multiple the lag is 18 days). For the combined multiples (OPE+D&A)/EV, and CF-multiples are chosen because of their relative outperformance in the main sample. S/EV, and E(Adj.)/P are chosen because of their common use by academics and practitioners. E(Adj.)/EV is chosen to provide an additional angle to the EV and equity-based multiples comparison. For all the composite multiples 6-month lagging momentum is used because of its relative outperformance against the other momentum metrics.

Table 6 Multiples in the Momentum sample

Implemented multiple	Consists of
Mome_12- 1m	12-month momentum with 1-month lag
Mome_12m	12-month momentum
Mome_6-1m	6-month momentum with 1-month lag
Mome_6m	6-month momentum
Mome_3m-1	3-month momentum with 18 days lag
Mome_3m	3-month momentum
(OPE+D&A)/EV	Operating income + Depreciation / Enterprise value
CF/P	Operating Cash Flow/ Market Capitalization
S/EV	Net Sales/ Enterprise value
E(Adj.)/P	Adjusted Net income/ Market Capitalization
CF/EV	Operating Cash Flow/ Enterprise value
E(Adj)/EV	Adjusted Net income/ Enterprise value
CF/EV + M	Ranking scheme of CF/EV and Mome_6-1m
CF/P + M	Ranking scheme of CF/P and Mome_6-1m
(OPE+D&A)/EV + M	Ranking scheme of (OPE+D&A)/EV and Mome_6-1m
E(Adj.)/EV + M	Ranking scheme of E(Adj.)/EV and Mome_6-1m
E(Adj.)/P + M	Ranking scheme of E(Adj.)/P and Mome_6-1m
S/EV + M	Ranking scheme of S/EV and Mome_6-1m
CF/EV + M 50/50	50/50 allocation between CF/EV and Mome_6-1m
CF/P + M 50/50	50/50 allocation between CF/P and Mome_6-1m
(OPE+D&A)/EV + M 50/50	50/50 allocation between (OPE+D&A)/EV and Mome_6-1m
E(Adj.)/EV + M 50/50	50/50 allocation between E(Adj.)/EV and Mome_6-1m
E(Adj.)/P + M 50/50	50/50 allocation between E(Adj.)/P and Mome_6-1m
S/EV + M 50/50	50/50 allocation between S/EV and Mome_6-1m

4.2.3 Forward-looking portfolios

Firm's current value is equal to its discounted future cash flows. Practitioners use most of the time forward-looking valuation multiples when they asses the cheapness/expensiveness of a stock. These forward-looking multiples are based on analyst estimates. For example, 12-month forward-looking EBIT/EV compares the firm's estimated EBIT in the next twelve months-to-enterprise value. Multiples in the forward-looking sample are based on the forward-looking financial attributes that could be found in the Refinitiv Eikon database.

In the forward-looking portfolios four different samples are used to make comparison of forward-looking strategies to past looking strategies more fruitful. The samples are the aforementioned: Fo_S EBIT, Fo_S EBITDA, Fo_S E(Adj.) and Fo_S Sales -samples. For example, the Fo_S EBIT sample has all the values for the operating income, EBIT, and forward-looking EBIT. Past looking OPE/EV and (OPE+D&A)/EV are also considered because they are adjusted financial metrics for EBIT and EBITDA. Forward-looking EBIT and EBITDA are expected to be cleaned from the non-operating costs and incomes.

Table 7 Multiples in the Forward-looking sample

Implemented multiple	Consists of
LTM_EBIT/EV	Last 12-month EBIT/EV
LTM_EBITDA/EV	Last 12-month EBITDA/EV
LTM_S/EV	Last 12-month S/EV
LTM_E/EV	Last 12-month E(Adj.)/EV
LTM_E/P	Last 12-month E(Adj.)/EV
LTM_OPE/EV	Last 12-month OPE/EV
LTM_(OPE+D&A)/EV	Last 12-month OPE+D&A/EV
12F_S/EV	12-month forward-looking S/EV
12F_EBIT/EV	12-month forward-looking EBIT/EV
12F_EBITDA/EV	12-month forward-looking EBITDA/EV
12F_E/P	12-month forward-looking E(Adj.)/EV
12F_E/EV	12-month forward-looking E(Adj.)/EV

4.3 Performance evaluation

Gross total returns are used to calculate portfolio's performance and thus we do not consider taxes or the transaction costs. As a risk-adjusted performance measures are used Sharpe ratio, Sortino ratio and modified Sortino ratio, Sortino_F ratio. As a main raw return measure, we use compound average growth rate (CAGR) which is annualized cumulative raw return for the whole observation period. CAGR is computed as follows:

$$R_p = \ (P_{i,t}/P_{i,t0})^{(\frac{1}{t})} - 1,$$

where *t* is the number of observation years. $P_{i,t}$ is the portfolio value at the end of the observation period and $P_{\mathrm{i,t0}}$ is the portfolio value in the beginning of the observation period.

Market-adjusted returns are a simple way to measure abnormal returns for the portfolios compared to the benchmark portfolio. To measure the performance of the value investing strategy that focuses on specific sector it is important to know if the performance differs relative to the sector performance and not only compared to the overall market performance. The market-adjusted returns here are calculated against the corresponding technology sector portfolio. First, the daily market-adjusted returns are computed as follows:

$$MARET_{i,t} = RAWRET_{i,t} - MKTRET_{Mkt,t},$$

Where $RAWRET_{i,t}$ is the daily return of the portfolio i and $MKTRET_{Mkt,t}$ is the daily return of the corresponding sample technology sector market portfolio. Next, market adjusted compounding average growth rates are computed by creating portfolios from the daily market-adjusted returns. CAGR is computed on the market-adjusted return portfolios to end up at the yearly market-adjusted returns.

The risk-adjusted performance measures are following Davydov et al. (2016) methodology. The first risk-adjusted return measure is the traditional Sharpe (1966) ratio. Sharpe ratio is widely used in value anomaly literature. To avoid the problems arising from the negative excess returns, the denominator is refined as suggested by Israelsen (2005). By raising σ_p to the power $\frac{ER}{|ER|}$ we can compare the negative Sharpe ratios as well. Sharpe ratio is computed as follows:

$$S_p = \frac{R_p - R_f}{\sigma_p^{\left(\frac{ER}{|ER|}\right)}},$$

where σ_p is the standard deviation of daily excess returns of portfolio p. R_f is risk free rate (12-month Euribor) and R_p is the compound annual growth rate of portfolio p. $R_p - R_f$ is known as the equity risk premium. ER is excess return. Sharpe ratio measures the excess returns in relation to the risk carried, in other words reward-to-risk ratio. Volatility of the excess returns is used as the risk measure.

The Sharpe ratio is widely used measure of performance by the academics and practitioners, but it has been also criticized for penalizing very high positive returns as they also increase the standard deviation (Goetzmann et al., 2007). Sortino ratio acknowledges this issue. It only uses negative returns to measure risk (Sortino and Van der Meer 1991; Sortino and Price 1994). The Sortino ratio applies the root-mean-square deviation below the minimum acceptable return. In this study, the risk-free rate is used as the minimum acceptable return. Sortino ratio is formulated as follows:

$$SR_p = \frac{R_p - MAR}{\sqrt{\frac{1}{n}\sum_{R_p<MAR}(R_p - MAR)^2}},$$

where MAR is Minimum acceptable return which is 12-month Euribor total return index. n is the number days when $R_p < MAR$.

Sortino ratio penalizes stocks with low number of down-days (days when $R_p - MAR$ is negative) because in the denominator $\sum_{R_p<MAR}(R_p - MAR)^2$ is divided by n. But in real-life investors appreciate having less down-days obviously. In addition, we can argue that the mean of the down-days is also important. This leads us to introduce a modified version of the Sortino ratio to measure downward deviation, the Sortino_F ratio. Additional benefit from using the Sortino_F ratio compared to Sharpe ratio is that it doesn't rely on standard deviation, so the results are less affected by the potentially asymmetric return distribution. The ratio is formulated as follows:

$$SFR_p = \frac{R_p - MAR}{\frac{DD_p}{DD_m}((\frac{1}{n}\sum_{R_p<MAR}(R_p - MAR))(-1))},$$

Where DD_m is the number of down-days *($R_p < MAR$)* for the Nordic market index. DD_p is the number of down-days for the portfolio p. $((\frac{1}{n}\sum_{R_p<MAR}(R_p - MAR))$ is the mean of the portfolio p down-day returns.

Additionally, to these portfolio performance measures, Fama and French (2015) three-factor model is used to measure abnormal returns to control whether the possible outperformance of the different strategies can be explained by asset pricing model's factors. FF3 seeks to explain returns with three risk factors: Market factor (MKT), size factor (SMB) and value factor *(HML)*. *MKT* measures the risk exposure for the market, *SMB* measures the exposure for the small capitalization stocks and *HML* the exposure for the high B/P stocks. To measure the excess returns of the portfolios we can write the FF3 model as time-series regression as follows:

$$R_i - R_f = \alpha_i + b_i(MKT) + s_i(SMB) + h_i(HML),$$

where $(R_m - R_f)$ is the risk premium, SMB is the size factor (small minus big) and *HML* is the value factor (high minus low). Value factor and size factors are created following

Fama and Franch (1998) methodology. Value portfolio used in the study is MSCI Nordic Countries Value Gross Index and as the growth portfolio is used MSCI Nordic Countries Growth Gross Index. As the small cap index is used FTSE Nordic Small Cap GI and as the large cap index is used FTSE Nordic Large Cap GI. All indices also consider dividends. All indices are obtained from Refinitiv Eikon. Then the value factor HML is the difference between value and growth portfolio returns and the SMB factor is calculated by subtracting the large cap portfolio returns from the small cap portfolio.

5 EMPIRICAL RESULTS

5.1 Descriptive statistics

This section provides five different kinds of descriptive statistics. Summary statistics for the important market indices, historical valuation levels of the firms during the study span, subsector and industry composition of the Nordic technology sector as well as the sub-sectors performance and the profitability of the firms. First, the summary statistics for the sample indices and FTSE Nordic Small Cap GI (Nordic Small Cap) and FTSE Nordic All Cap GI (Nordic All Cap) are reported. From Table 8 can be seen that the main sample market produced high abnormal returns compared to the Nordic All Cap and Small Cap index. This supports the statement that the technology sector has performed exceptionally well during the last 15 years, especially after 2015. As can be seen from Figure 6, until 2015 the performance of the Nordic Small Cap, Nordic All Cap, Market_Main and Market_Mome went pretty much hand in hand. The forward-looking samples on the other hand were underperforming against these four indices. After 2015, all the technology sector indices overperformed the Nordic Small Cap and Nordic All Cap indices.

The risk-adjusted returns are telling the same story. The higher returns by the technology sector are generated with lower volatility as well. The Sharpe ratios for the main sample are 2.77 and 2.32 times the Sharpe ratios of the All cap and Small cap indices. The downside volatility measures Sortino and Sortino_F ratios are telling the same story. However, the returns of the technology sector are asymmetric in unfavorable way for the investor as they exhibit quite high negative skewness and high kurtosis. All though, as can be seen from Table 8, skewness and kurtosis for the pre-Covid period are considerably closer to the All cap and Small cap indices.

Table 8 Summary statistics for the sample markets and FTSE Nordic Small Cap GI and FTSE Nordic All Cap GI indices

The table reports summary statistics for the sample markets and FTSE Nordic Small Cap GI and FTSE Nordic All Cap GI indices from the 31st of March 2006 until the 1st of April 2021. In the parenthesis are reported measures for pre-Covid-19 period. Pre-Covid period lasts until 31st of January 2020. The measures have been computed using raw daily returns. Thus, there are 3813 daily observations for the full analysis period and 3516 observations for the pre-Covid-19 period. Standard deviation, Sharpe ratio, Sortino ratio and Sortino_FR have been annualized assuming 252 trading days. Risk-free rate and minimum acceptable return used for calculating Sharpe ratio and Sortino ratio is 12-month Euribor. Below in Figure 6 the performance of the indexes of the table is presented.

Index	CAGR	Stdev	Skew-ness	Kurto-sis	Sharpe ratio	Sortino ratio	Sortino_FR	n
Market_Main	15.5% (11.9%)	14.7% (13.5%)	-1.42 (-0.70)	14.30 (6.40)	0.98 (0.78)	0.86 (0.62)	1.62 (1.30)	3813 (3516)
Market_Mome	14.7% (11.0%)	14.8% (13.7%)	-1.37 (-0.66)	14.05 (6.22)	0.91 (0.70)	0.82 (0.57)	1.51 (1.17)	3813 (3516)
Market_Fo_s_EBIT	12.5% (8.9%)	14.8% (13.8%)	-1.17 (-0.65)	11.47 (6.29)	0.76 (0.55)	0.68 (0.44)	1.26 (0.94)	3813 (3516)
Market_Fo_s_EBITDA	13.1% (9.5%)	14.9% (13.9%)	-1.15 (-0.63)	11.47 (6.35)	0.80 (0.59)	0.72 (0.48)	1.32 (0.99)	3813 (3516)
Market_Fo_s_E(Adj.)	13.2% (9.6%)	14.8% (13.7%)	-1.30 (-0.70)	12.72 (6.55)	0.81 (0.61)	0.72 (0.48)	1.36 (1.03)	3813 (3516)
Market_Fo_s_S	13.3% (9.8%)	14.7% (13.6%)	-1.33 (-0.71)	13.13 (6.48)	0.82 (0.62)	0.73 (0.49)	1.37 (1.06)	3813 (3516)
FTSE Nordic Small Cap GI	10.2% (9.1%)	22.1% (21.3%)	-0.55 (-0.31)	6.86 (5.23)	0.41 (0.36)	0.37 (0.31)	0.66 (0.61)	3813 (3516)
FTSE Nordic All Cap GI	8.3%	22.2%	-0.20	5.99	0.32	0.31	0.53	3813

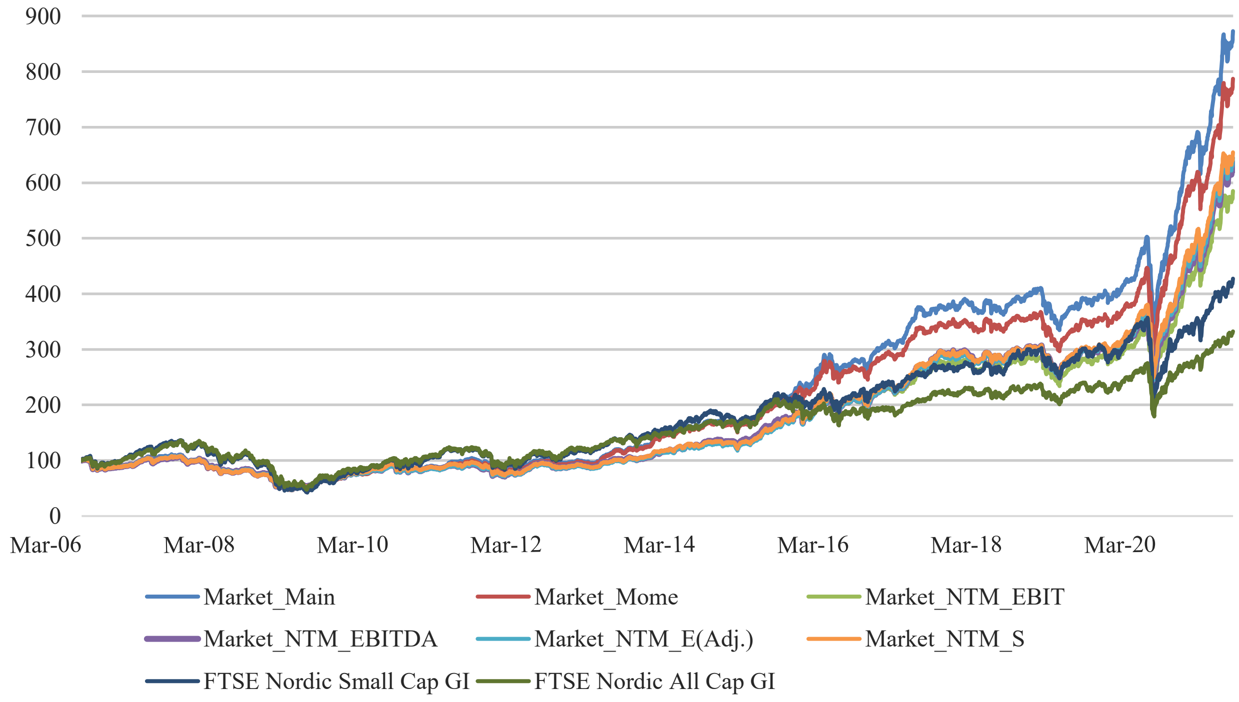

Figure 6 Performance of the samples, FTSE Nordic Small Cap GI and FTSE Nordic All Cap GI indices

Next, the valuation levels are reported from two samples: main sample and the forward-looking sample. Forward-looking sample is reported in addition because its components are more stable compared to the main sample. The forward-looking sample also consist of more liquid set of stocks. Additionally, forward-looking valuation ratios can be only derived from the forward-looking sample. The reported multiples are the most common ones in the value investing literature as well as the most used by practitioners: E/P, P/B, EV/Sales and EV/EBIT.

Figure 7 presents P/E(Adj.), EV/EBIT, P/B and EV/Sales for the main sample on the portfolio formation date. The ratios are presented in this format to make comparison between ratios easier. Only positive observations are considered. If we compare the valuation levels with Figure 15's bull and bear markets, we can observe that the valuation levels have been approximately depreciating during the bear markets and appreciating during the bull markets. Overall, the trend has been increasing valuation levels after the Euro crisis 2012. The 2019 and 2020 depreciating levels in the EV/Sales and EV/EBIT are linked probably to two main factors: strong corrections in the market before portfolio formation day and increasing number of companies with strong balance sheets. Strong balance sheets (negative net debt) are due the large number of new IPOs where companies gather cash by selling new stock to the new shareholders. The fact that P/E and P/B ratios increased in 2019 as EV/Sales and EV/EBIT ratios decreased supports this assumption.

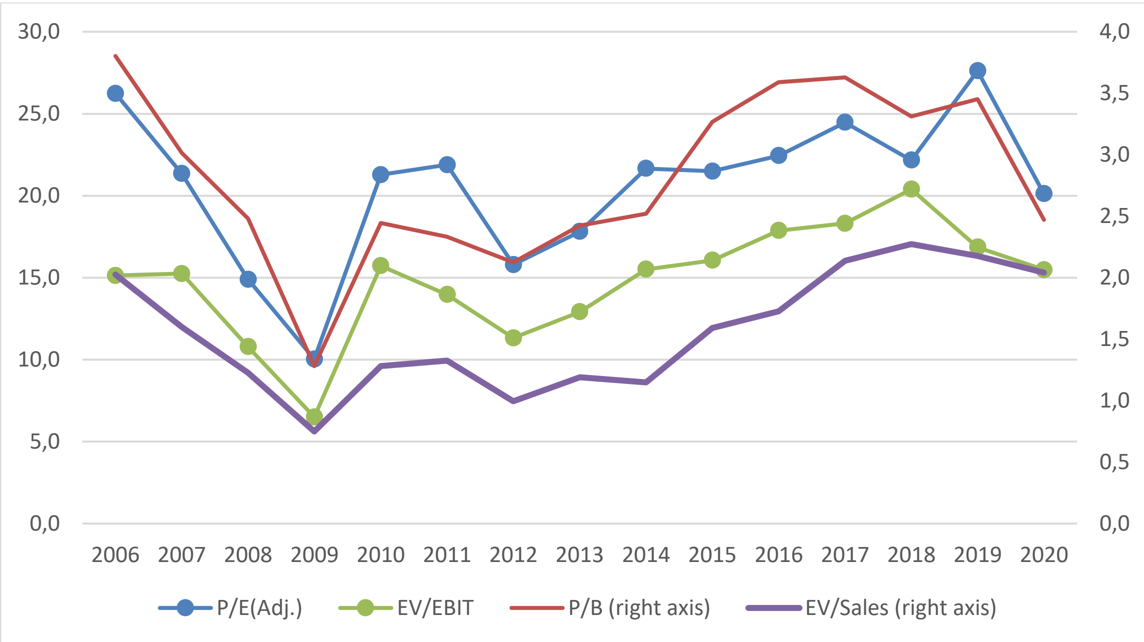

Figure 7 Median (excluding negatives) P/E(Adj.), EV/EBIT, P/B and EV/Sales for the main sample

Figure 8 reports 12F P/E, P/E(Adj.), 12F EV/Sales and EV/Sales ratios for the forward-looking sample. For the steadier EV/Sales ratios, can be observed that the forward-looking and past-looking multiples diverse more in the bull markets and converge during the bear markets. This implies, that the future growth expectations are lower during the bear markets and higher during the bull markets. Additionally, this could be implying that the investors give more value to the near term and realized revenues than the uncertain expected future revenues. Interesting note about the 12F P/E ratio is that it peaked in 2017. However, because the graph considers only the positive occurrences and many of the newly listed companies does not produce earnings, no trustworthy conclusions can be derived from the graphs.

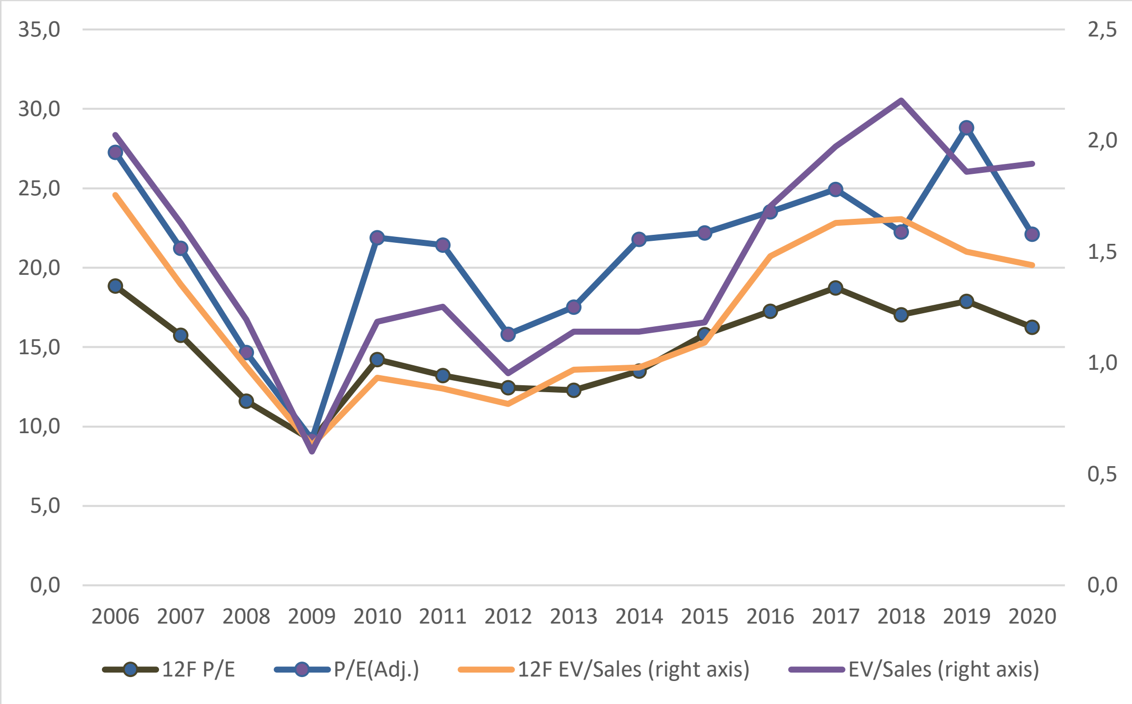

Figure 8 Median (excluding negatives) P/E(Adj.), 12F P/E, EV/Sales and 12F EV/Sales for the main sample

Subsequently, the sector and industry composition of the Nordic technology sector is studied in more detail. This is done by investigating the ICB industry and ICB sector classifications of the companies. The main sample with 332 unique firms is studied in more detail. Figure 9 presents the main sample ICB industry composition. The composition is dominated by technology industry but as can be seen in the graph the technology share decreases from 68.1% in 2006 to 53.9% in 2020. Another loser in percentage share over the years is telecommunications which goes from 12.4% in 2006 to 9-4% in 2020.

Only significant winner industry in the relative importance is consumer discretionary which goes from 3.5% in 2006 to 16.0% in 2020.

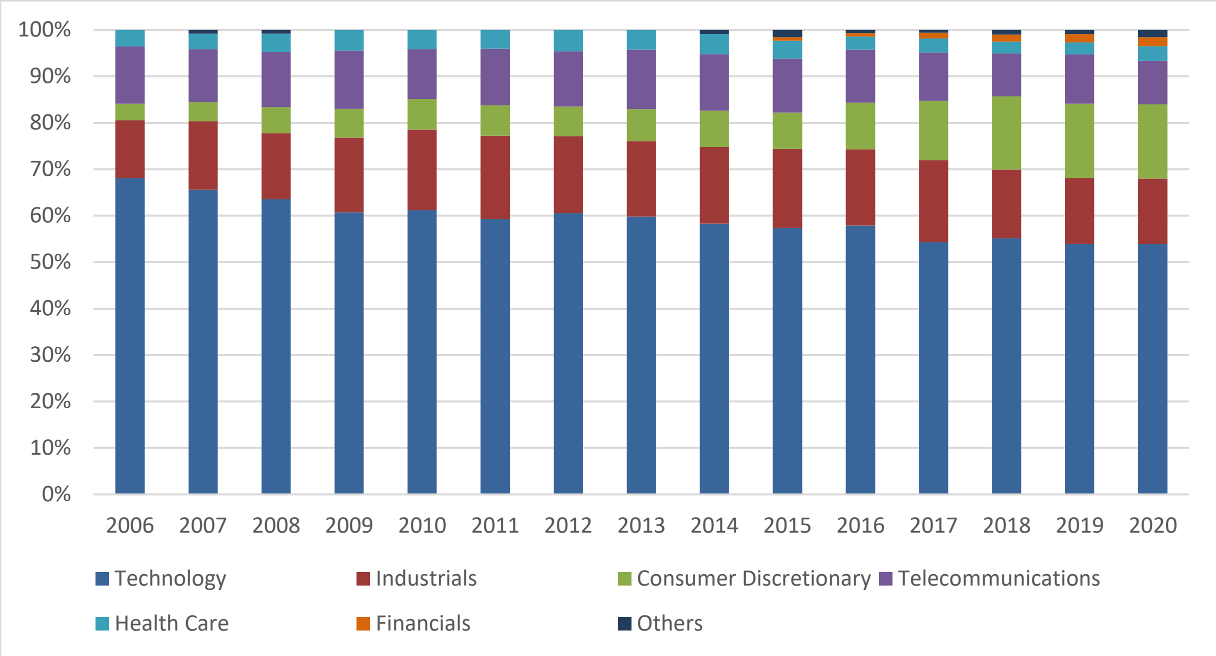

Figure 9 ICB industry classifications of the main sample firms

In addition, the ICB sector classifications are studied in the main sample. Figure 10 reports the ICB sector classifications for the main sample firms. Nordic technology sector is dominated by *software and computer services* sector although it loses some relative importance throughout the years because in the other sectors the number of companies increases relatively more. Four other important ICB sectors in the Nordic technology sector are *technology hardware and equipment, electronic and electrical equipment, telecommunications equipment and leisure goods*. Especially *leisure goods* have increased in relative importance throughout the years. Another insight that can be derived from this data is that the Nordic technology sector is significantly more heterogenic in 2020 compared to 2006. *Other* category accounted only for 7.1% in 2006 but in 2020 it accounted already for 16.8%.

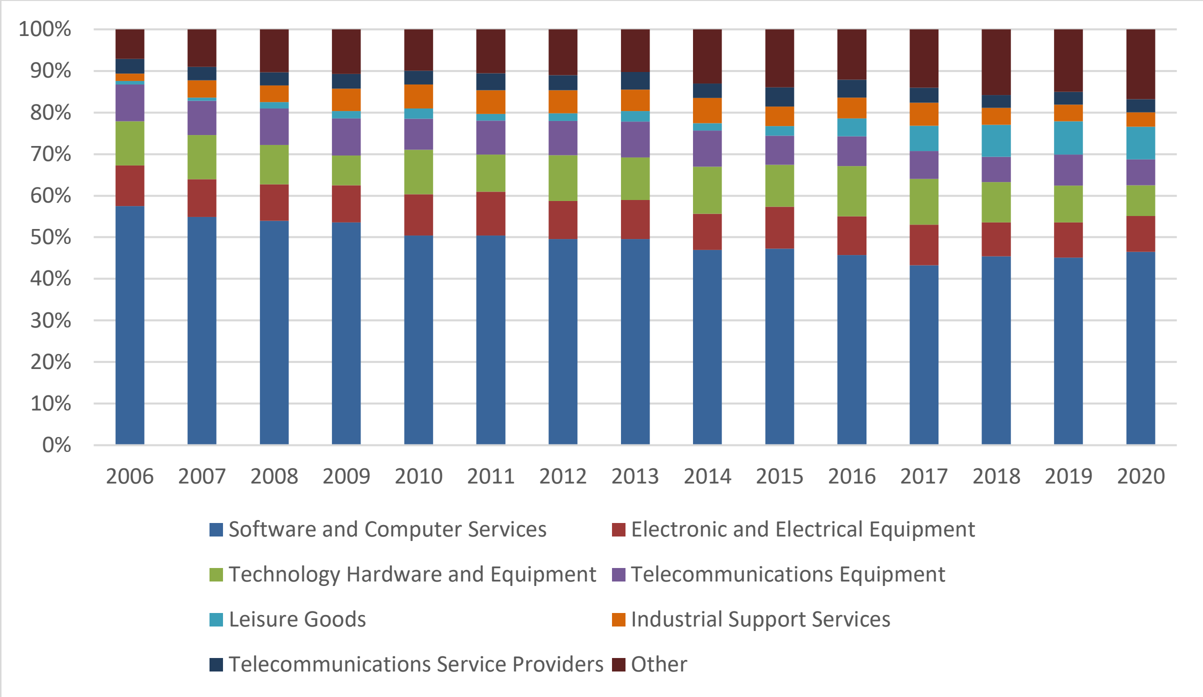

Figure 10 ICB sector classifications of the main sample firms

Next, performance of the most important subsectors is examined. Table 9 and Figure 11 presents the performance of the subsectors. The largest sector *Software and computer services* outperformed the overall Nordic technology sector as well as the other subsectors. *Software and services* generated an outstanding 17.5% CAGR and 1.12 Sharpe ratio. Significant outperformance of the total Nordic technology sector (15.5% and 0.98). Next three biggest subsectors *Electronic and Electrical Equipment* (10.3% and 0.36), *Technology Hardware and Equipment* (11.9% and 0.38) and *Telecommunications* (9.5% and 0.38) underperformed compared to the Nordic technology sector. Other category performance was approximately on the same level as the Nordic technology sector. However, it good to take these results, especially the risk-adjusted metrics, with a grain of salt because in all the subsectors (except in *Software and services* which dominates the sector) the number of companies is low and varies yearly. It seems like the technology subsectors which are less capital intensive have performed better.

Table 9 Descriptive statistics for the most important technology subsectors

Sector classifications are ICB sector classifications except Telecommunications is ICB industry classification which includes ICB sectors Telecommunications equipment and Telecommunications service providers. In the parenthesis are reported measures for pre-Covid-19 period. Pre-Covid period lasts until 31 January 2020. The measures have been computed using raw daily returns. Thus, there are 3813 daily observations for the full analysis period and 3516 observations for the pre-Covid-19 period. Standard deviation, Sharpe ratio, Sortino ratio and Sortino_FR have been annualized assuming 252 trading days. Risk-free rate and minimum acceptable return used for calculating Sharpe ratio and Sortino ratio is 12-month Euribor. Other category also includes Leisure goods and Industrial support services from the Figure 11.

Sector	CAGR	Stdev	Skewness	Kurtosis	Sharpe ratio	Sortino ratio	Sortino_FR
Software and computer services	17.5%	0.91%	-1.23	13.16	1.12	1.02	1.73
	13.7%	0.83%	-0.60	5.51	0.94	0.75	1.37
Electronic and Electrical Equipment	10.3%	1.60%	0.28	4.81	0.36	0.37	0.49
	9.2%	1.58%	0.49	4.36	0.31	0.31	0.43
Technology Hardware and Equipment	11.9%	1.79%	0.04	11.08	0.38	0.38	0.52
	8.3%	1.76%	0.25	11.67	0.25	0.24	0.35
Telecommunications (ICB industry name)	9.5%	1.49%	0.98	15.55	0.35	0.38	0.51
	6.3%	1.41%	1.30	17.33	0.22	0.22	0.31
Other	16.3%	1.19%	-0.04	11.21	0.80	0.80	1.19
	12.2%	1.14%	0.50	9.34	0.60	0.56	0.87

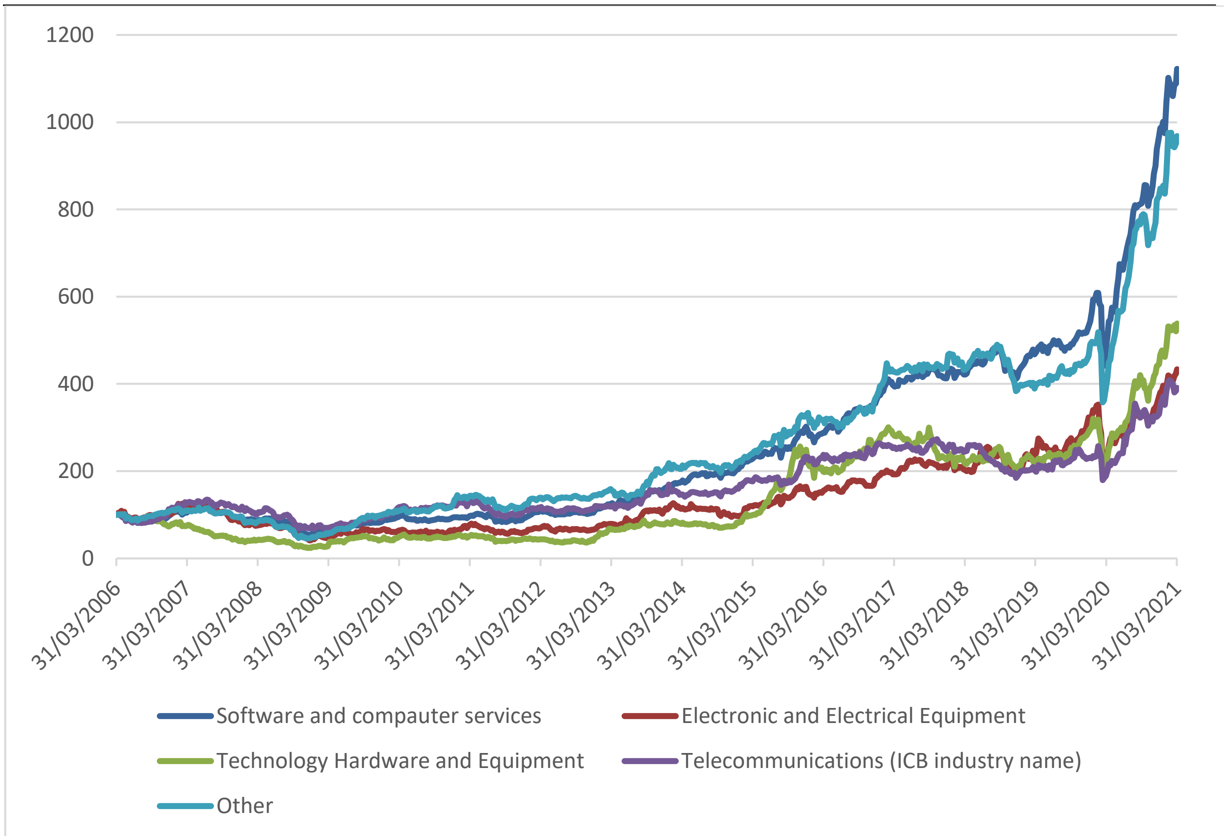

Figure 11 Performance of the most important technology subsectors

To conclude this section, the profitability of the main sample firms is studied. The technology sector firms are often characterized as fast-growing companies with low profitability. Figure 12 which reports the percentages of positive earnings on different earnings or cash flow levels confirms this assumption. The profitability levels stayed somewhat stable from 2006 until 2016 if the financial crisis is excluded. In 2017 the share of firms with positive earnings went into steep decline. If we look at the share of firms with positive net income, the share went from 74.3% in 2006 to 47.3% in 2020. There is some divergence in the share of the of firms with positive earnings depending on which earnings metric is applied. In 2020, on net income level 47.3% of the firms were positive, on EBIT level 50.4%, on EBITDA level 60.9% and on operating cash flow level 57.8%. These results are suggesting that multiples that are based on EBITDA or operating cash flow might be more relevant in the Nordic technology sector.

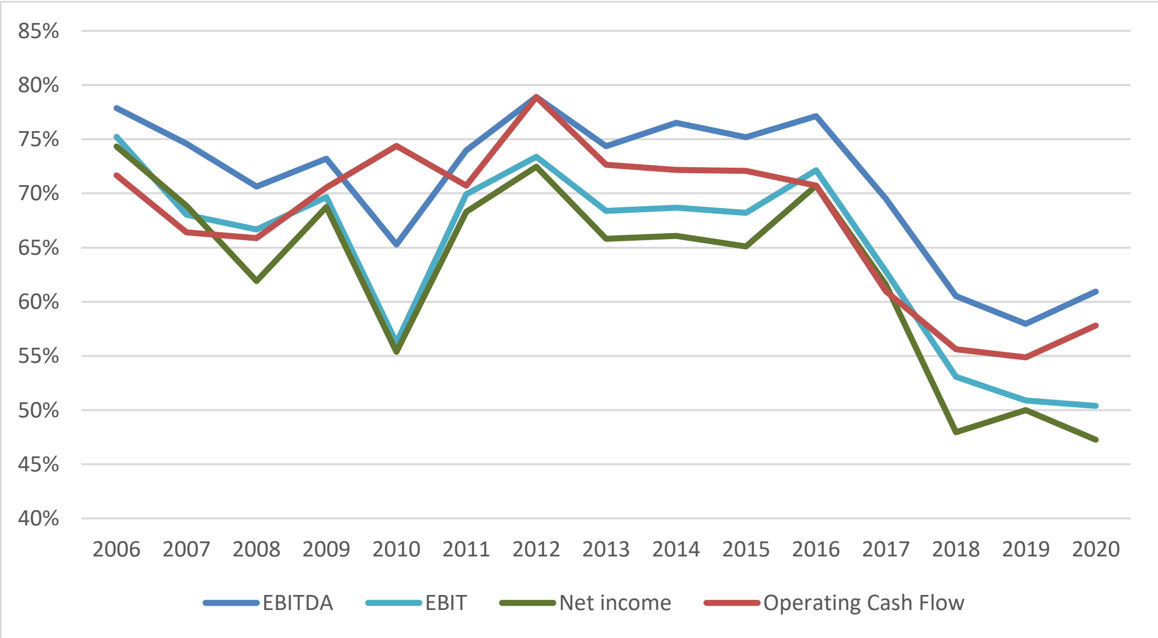

Figure 12 Percentage of firms with positive earnings on different levels

The figure displays percentage of firms with positive earnings or cash flow relative to the total sample. The reported numbers are from the main sample.

5.2 Performance of the strategies

5.2.1 Performance of the main sample strategies

In this section, the returns for the main sample strategies are reported. Furthermore, the market-adjusted returns are analyzed along with risk-adjusted measures Sharpe, Sortino and Sortino_F ratio. In addition, enterprise value-based versus market capitalization-based and operating-adjusted versus non-adjusted multiples are compared, as well as the complete observation period versus pre-Covid period. Table 10 presents the returns for the one-year buy-and-hold strategies with different multiples. The market-adjusted returns are calculated against the main sample overall portfolio (in other words: Nordic technology sector). Three different strategies are presented for all the multiples: top 30%, top 20%, and top 20 strategies. The focus is on the top 20% (top quintile with highest valuation ratios) strategies. If top 30%, top 20%, or top 20 portfolio is not specified, reader can assume that we speak about top 20% portfolio.

Market CAGR for the period was 15.5%. In the top 20% portfolios 17/18 of the multiples produced higher returns than the market. Only S/P had lower CAGR (15.0%) than the market. In addition, D/P multiple produced negative market-adjusted returns. The multiples could be divided loosely into four performance groups. Group 1 includes *OPE+D&A/EV (CAGR 24.0%), CF/EV (23.8%)* and *CF/P (22.8%).* Group 1 multiples are quite clearly superior compared to the other multiples, they produced yearly 7.0%, 6.9% and 6.0% technology market-adjusted returns, respectively. Group 2 includes *OPE+D&A/P (20.8%), E(Adj.)/EV (20.9%), EBITDA/EV (20.4%), OPE/EV (20.2%) and EBITDA/P (19.8%).* Group 2 also produced significant yearly 4.3-3.4% market-adjusted returns. Group 3 includes *OPE/P (19.0%), E(Adj.)/P (19.8%), EBIT/EV (18.6%), E/P (18.5%) and S/EV (18.2%).* Group 3 produced as well respectable market-adjusted returns ranging from 3.5% to 2.1%. Here, a bit of an outlier is the *E(Adj.)/P* multiple which produced 3.5% market-adjusted returns, but it produced them with higher standard deviation and down-side deviation than the multiples in the group 2. Group 4 includes *EBIT/P (16.6%), D/P (15.9%), B/EV (16.5%), B/P (15.8%) and S/P (15.0%).* Group 4 market-adjusted returns vary from 0.7% to -0.8%. Interestingly, considering how widely multiples with the sales metric are used by the practitioners, S/P is the multiple with the worst performance which implies that is does not work well as a mechanical value strategy.

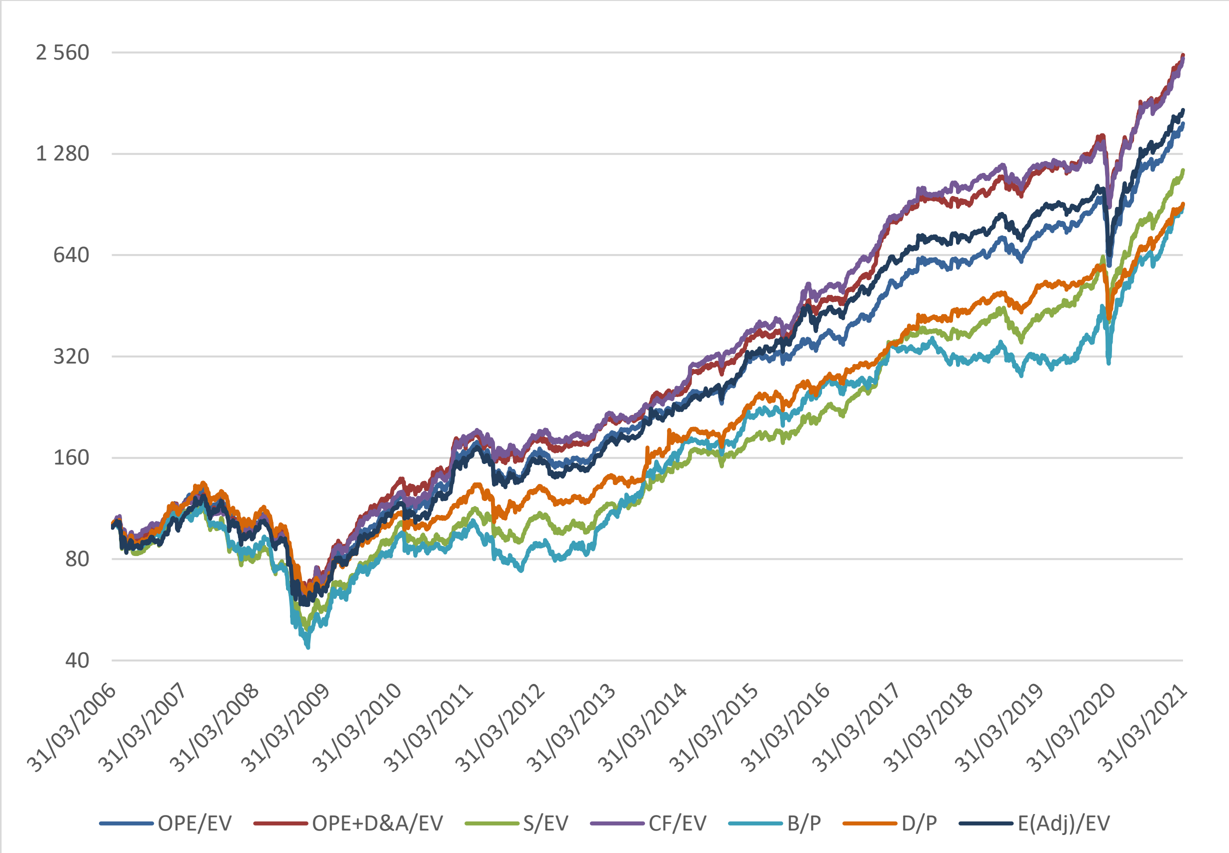

Figure 13 Performance of the selected multiples in the top 20% portfolios (logarithmic scale)

Risk-adjusted performance measures are telling the same story about the groups. In groups 1, 2 and 3 all the multiples outperform the market, except *S/EV* has lower Sortino_F ratio than the market. In the group 4 *EBIT/P* also outperforms market in all the risk-adjusted measures. *D/P* also outperforms the market in the Sortino ratio. Group 1 significantly outperforms the market with all the risk-adjusted measures. The leader *OPE+D&A/EV* producing 45.5% higher Sharpe, 56.1% higher Sortino and 46.5% Sortino_F ratio. This is especially remarkable considering how strong the performance of the market is. However, the portfolios exhibit quite high negative skewness and high kurtosis, which tilts the returns towards unfavorable asymmetry for the investors. All though, if we look at the pre-covid results the returns are closer to the normal distribution.

If the valuation multiple predicts future returns well, the portfolio returns for the multiple should increase if we compare top 20% portfolio to top 30% or top 20 portfolio to the top 20% portfolio. This metric (concentration-metric) emphasizes further the strong performance of *OPE+D&A/EV*. For the *CF-based* multiples clear improvement can be seen in the when comparing top 20% to top 30% but when comparing top 20 to top 20% CAGR and market-adjusted CAGR improve quite marginally but this offset by the higher volatility as risk-adjusted returns decrease. Another top performer looking by this concentration metric is *E(Adj.)/EV*.

Another interesting point in the results is the fact that the operating-adjusted financial metrics outperform the non-adjusted reported numbers. For example, *operating profit* clearly outperforms *EBIT* and *operating income + depreciation & amortization* outperforms *EBITDA.* This in intuitively very logical and the security analysts talk most of the time about the operating-adjusted valuation multiples. These empirical results seem to support this practice. The differences are significant, for example the Sharpe ratio for *OPE+D&A/EV* is 1.42 versus 1.17 of *EBITDA/EV*.

Another clear conclusion from the data is that enterprise value-based multiples outperform the market capitalization-based multiples. Interestingly, one of the biggest outperformers is *E(Adj.)/EV.* It clearly outperforms *E(Adj.)/P* within all the metrics. What makes this interesting is the fact that the famous P/E ratio is still the most used ratio by the financial world (Pinto et al. 2019). Also, not a single academic study could be found which studies E/EV metric. The performance could be merited for the fact that the markets are overlooking *E/EV* ratios. Another metric that is completely overlooked by the practitioners and the academics is *B/EV* ratio. *B/EV* also comfortably outperforms the *B/P,* which is still the main staple of the value investing literature. Market capitalization-based multiples produce lower volatility compared to their enterprise value counterparts except for *S/P*-to-*S/EV.* The higher volatility is compensated by proportionally higher returns by the EV-based multiples, which can be seen from the clearly higher risk-adjusted returns. Overall, the data supports the claim that investors should also consider the leverage of the firm when evaluating the stock's valuation. This is contrary to Scheiner (2007) results who studied value relevance of the valuation multiples. He found that market capitalization-based multiples outperform EV-based multiple in 15/16 multiples. His main measure of performance was the median valuation error.

Table 10 Returns for the main sample

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current sample market. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the main sample market. The multiples are ranked according to the Top 20% -portfolios Sortino ratio. Except market returns are reported first. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios. Only Top 20% portfolios are reported here, Top 30%, and Top 20 portfolios are reported in the Appendix 1.

Top20%	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F
Market	15.5%	0.0%	0.92%	-1.42	14.30	0.98	0.86	1.49
	11.9%	*0.0%*	*0.85%*	*-0.70*	*6.40*	*0.78*	*0.62*	*1.16*
OPE+D&A/EV	24.0%	7.0%	1.01%	-0.75	10.08	1.42	1.34	2.19
	21.0%	*7.8%*	*0.93%*	*-0.19*	*4.65*	*1.33*	*1.12*	*1.98*
CF/EV	23.8%	6.9%	1.02%	-0.77	9.55	1.39	1.29	2.14
	20.6%	*7.5%*	*0.94%*	*-0.30*	*4.47*	*1.29*	*1.07*	*1.91*
CF/P	22.8%	6.0%	1.01%	-0.88	10.22	1.35	1.24	2.08
	20.2%	*7.1%*	*0.94%*	*-0.26*	*4.70*	*1.26*	*1.06*	*1.89*
OPE+D&A/P	20.8%	4.3%	1.02%	-0.58	9.16	1.21	1.15	1.83
	18.1%	*5.3%*	*0.97%*	*0.02*	*4.79*	*1.10*	*0.96*	*1.62*
E(Adj)/EV	20.9%	4.5%	1.05%	-0.61	7.41	1.19	1.12	1.79
	18.0%	*5.2%*	*0.98%*	*-0.27*	*4.41*	*1.07*	*0.91*	*1.57*
EBITDA/EV	20.4%	4.0%	1.04%	-0.60	11.53	1.17	1.11	1.77
	17.3%	*4.5%*	*0.96%*	*0.07*	*5.80*	*1.04*	*0.89*	*1.54*
OPE/EV	20.2%	3.7%	1.00%	-0.83	9.03	1.19	1.11	1.81
	17.5%	*4.7%*	*0.93%*	*-0.40*	*4.57*	*1.09*	*0.91*	*1.61*
EBITDA/P	19.8%	3.4%	1.01%	-0.55	9.74	1.15	1.09	1.73
	16.9%	*4.1%*	*0.96%*	*0.09*	*5.14*	*1.01*	*0.88*	*1.49*
OPE/P	19.0%	2.7%	0.99%	-0.84	9.36	1.13	1.05	1.71
	16.7%	*4.0%*	*0.93%*	*-0.28*	*4.88*	*1.04*	*0.88*	*1.53*
E(Adj.)/P	19.8%	3.5%	1.04%	-0.66	7.52	1.12	1.04	1.68
	17.6%	*4.9%*	*1.00%*	*-0.21*	*4.50*	*1.03*	*0.89*	*1.52*
EBIT/EV	18.6%	2.4%	1.00%	-0.78	11.91	1.09	1.03	1.67
	16.0%	*3.3%*	*0.93%*	*-0.09*	*5.38*	*0.99*	*0.83*	*1.47*
E/P	18.5%	2.3%	1.02%	-0.63	8.65	1.07	1.00	1.61
	16.3%	*3.7%*	*0.97%*	*-0.10*	*4.54*	*0.97*	*0.83*	*1.42*
S/EV	18.2%	2.1%	1.09%	-0.66	11.05	0.98	0.95	1.45
	14.2%	*1.8%*	*1.01%*	*-0.07*	*4.00*	*0.80*	*0.70*	*1.13*
EBIT/P	16.6%	0.6%	0.97%	-0.84	11.95	1.00	0.93	1.51
	14.4%	*1.9%*	*0.91%*	*-0.10*	*5.50*	*0.90*	*0.76*	*1.32*
D/P	15.9%	-0.1%	0.99%	-0.80	8.03	0.93	0.90	1.44
	13.5%	*1.1%*	*0.96%*	*-0.33*	*4.10*	*0.80*	*0.72*	*1.22*
B/EV	16.5%	0.7%	1.16%	-0.26	6.78	0.83	0.84	1.18
	12.4%	*0.3%*	*1.08%*	*0.04*	*2.55*	*0.65*	*0.59*	*0.88*
B/P	15.8%	0.1%	1.16%	-0.28	7.45	0.80	0.80	1.13
	10.8%	*-1.2%*	*1.09%*	*0.11*	*3.23*	*0.55*	*0.50*	*0.75*
S/P	15.0%	-0.8%	1.07%	-0.72	11.17	0.81	0.78	1.18
	11.5%	*-0.7%*	*0.99%*	*-0.09*	*4.02*	*0.64*	*0.56*	*0.90*

How about the performance before Covid-19 crisis? After the beginning of the Covid-19 crisis the volatility increased massively in the markets and a lot of thought to be very small probability events took place in a short time span. The volatility was offset by even higher returns if we measure the offsetting by the risk-adjusted measures. All multiples performed better if we look at the risk-adjusted measures in every category when comparing total observation period to the pre-Covid period. More interesting question here is: How the market-adjusted returns changed if we compare the periods? For the top 30% and top 20% portfolios, only 3/18 multiples, the ones with the highest volatility, produced higher market-adjusted returns for period which includes Covid-19 crisis. These multiples being *B/EV, B/P and S/EV.* For the more concentrated top 20 portfolios, in addition to these three multiples, *OPE+D&A/EV, EBITDA/EV* and *S/P* produced higher market-adjusted returns. From this evidence we can say that the overall technology sector performed extremely well after the beginning of the Covid-19 crisis. The studied value investing strategies in general performed better in the more "regular" market settings if we compare them to the overall sector. The risk-adjusted measures recorded higher values for the total observational period. This is due the exceptionally high returns after the beginning of the Covid-19 crisis.

5.2.2 Performance of the momentum sample strategies

In this section, the returns for the momentum sample are reported. All the measures are analyzed from the perspective of whether incorporating momentum can improve the value strategies. Correlation matrix is also presented for the momentum sample multiples. *OPE+D&A/EV, CF/EV, CF/P, E(Adj.)/EV, E(Adj.)/P* and *S/EV* are chosen to the comparison. *OPE+D&A/EV, CF/EV* and *CF/P* are chosen because of their superior performance in the main sample which makes them the most interesting multiples. *E(Adj.)/EV* and *E(Adj.)/P* are chosen because of their similar performance compared to the momentum and *S/EV* is chosen because it has the lowest correlation (except for *B/EV* and *B/P* with the momentum (see Table 11). *S/EV* is chosen over book value multiples because of its superior performance, and it is more used by the practitioners in the high growth industries.

Table 11 Correlation matrix for the momentum multiples within the top 20% portfolios

	Tech sector Momentum	***Nordic Small Cap***	***Momentum***	***CF/EV***	***P/CF***	***OPE+D&A/EV***	***E(Adj.)/EV***	***E(Adj.)/P***
Tech sector Momentum	1							
Nordic Small Cap	0.794	1						
Momentum	0.818	0.653	1					
CF/EV	0.793	0.696	0.637	1				
P/CF	0.797	0.716	0.642	0.928	1			
OPE+D&A/EV	0.788	0.683	0.646	0.853	0.840	1		
E(Adj.)/EV	0.803	0.717	0.644	0.826	0.808	0.863	1	
E(Adj.)/P	0.805	0.735	0.656	0.798	0.821	0.838	0.947	1
S/EV	0.770	0.620	0.604	0.720	0.728	0.723	0.678	0.682

First, let's look at the momentum performance in Table 14. 6-month momentum with 1-month lag would have been a group 2 performer in the *main sample*. The top 20% momentum portfolio CAGR (22.1%) is almost at the same level as *CF/EV* and higher than *CF/P*. Same applies to the market adjusted CAGR (6.6%). Momentum portfolio's returns are significantly more volatile which places its risk-adjusted measures at the group 2 level. The concentration-metric also improves when moving from the top 30% to the top 20% portfolio but deteriorates clearly when moving from the top 20% to top 20 portfolio. This implies the importance of the diversification when applying the pure-play momentum strategy. From Table 11 can be seen that the momentum portfolio correlation is higher with the technology sector but lower with the Nordic Small Cap index (except for the S/EV) than the selected multiples. Momentum anomaly seems to be present in the Nordic technology sector.

Ranking scheme improved 4/6 of the multiples in top 30% portfolios. The ranking scheme seems to work best when the selection of stocks is broader. The ranking scheme portfolios have significantly lower volatility than the corresponding pure-play value portfolios. This is interesting because momentum portfolios have significantly higher standard deviation than the value investing portfolios. For example, momentum top 20% portfolio standard deviation is 1.20% and *E(Adj.)/EV* 1.07%, but the ranking scheme portfolio standard deviation is 1.02%. The ranking scheme performs poorly in the top 20% and top 20 portfolios. Again, the standard deviation of the returns is lower for all the multiples compared to the sole multiple, but the risk-adjusted measures are improved only in the case of *E(Adj.)/P*. In the top 20 portfolios the story is the same but this time incorporating momentum improves only *S/EV*. According to our data there is only some evidence for using ranking scheme strategy if the portfolio concentration is broader.

50/50 strategy seems to be viable strategy. The portfolios are less volatile in all the cases. This is not surprising as the 50/50 strategies have exposure to more stocks compared to the sole multiple portfolios. However, this decrease in volatility is not offset by lower returns, as the 5/6 50/50 portfolios perform better than their sole multiple counterparts in the top 20% and top 20 portfolios if we look at the risk-adjusted measures. This result is similar to Assness et. al (2013) results, where they found that 50/50 portfolios improve the Sharpe ratios compared to the value portfolios. However, they only studied B/P portfolios. In the top 30% portfolios 3/6 of the 50/50 perform better than their sole multiple counterparts. The improvement of the performance comes mainly in the way of reducing volatility. The 50/50 strategy seems like a viable strategy for capturing the momentum premium in the markets. If we look at the risk-adjusted measures in the top 20% portfolios, all the composite portfolios are an improvement compared to the sole momentum portfolio. This is not trivial, because the CAGR of the momentum top 20% portfolio is 22.1% which is clearly better than most the of sole multiple portfolios excluding *CF/EV* and *OPE+D&A/EV*. Table 12 reports the summary of the improvement.

Table 12 Summary of composite value improvement over sole value multiple

Top 30%	CAGR	M-Ad. CAGR	Std. dev.	Sharpe	Sortino	Sortino_F
Ranking scheme	4/6	4/6	5/6	3/6	4/6	4/6
50/50	3/6	3/6	6/6	3/6	3/6	3/6
Top 20%						
Ranking scheme	0/6	0/6	6/6	1/6	1/6	1/6
50/50	5/6	5/6	6/6	5/6	5/6	5/6
Top 20						
Ranking scheme	1/6	1/6	6/6	1/6	1/6	1/6
50/50	3/6	3/6	6/6	5/6	5/6	5/6

Table 13 presents the comparison between the two momentum composite strategies. In the top 30% portfolios there is no clear edge over the other for either of strategies. However, in the top 20% and top 20 portfolios the picture is clear. 50/50 have a clear edge over the ranking scheme. Within all the multiples, returns and risk-adjusted returns are 6-0 in favor of 50/50 strategy. Interestingly, the standard deviation is still 4-2 in favor of ranking scheme strategy even though it has exposure to the lower number of stocks. This is due the fact that the standard deviation of the momentum portfolio is very high in the top 20% and top 20 portfolios (1.20% and 1.26%). We can conclude that the 50/50 strategy has an edge over the ranking scheme strategy, this especially true with more concentrated portfolios. However, it is good to note that the 50/50 strategy would incur probably more transaction costs as the portfolios have higher number of stocks.

Table 13 Summary of comparison between ranking scheme and 50/50 portfolios

Top 30%	CAGR	M-Ad. CAGR	Std. dev.	Sharpe	Sortino	Sortino_F
Ranking scheme	3	3	2	2	2	3
50/50	3	3	4	4	4	3
Top 20%						
Ranking scheme	0	0	4	0	0	0
50/50	6	6	2	6	6	6
Top 20						
Ranking scheme	0	0	4	0	0	0
50/50	6	6	2	6	6	6

Table 14 Returns for the momentum sample

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current sample market. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the momentum sample overall technology sector. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios. Only Top 20% portfolios are reported here, Top 30%, and Top 20 portfolios are reported in the Appendix 2.

Top 30%	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F
Market_Mome	14.7%	0.0%	0.93%	-1.37	14.05	0.91	0.82	1.39
	11.0%	*0.0%*	*0.86%*	*-0.66*	*6.22*	*0.70*	*0.57*	*1.03*
Mome_6-1m	22.1%	6.6%	1.20%	-0.62	8.75	1.10	1.05	1.63
	18.1%	*6.6%*	*1.14%*	*-0.18*	*6.00*	*0.93*	*0.82*	*1.35*
OPE+D&A/EV	25.3%	8.8%	1.03%	-0.65	9.63	1.47	1.39	2.27
	22.1%	*9.7%*	*0.95%*	*-0.11*	*4.62*	*1.37*	*1.16*	*2.06*
CF/EV	22.7%	6.7%	1.04%	-0.68	8.82	1.30	1.22	1.99
	19.4%	*7.3%*	*0.97%*	*-0.30*	*4.99*	*1.17*	*0.99*	*1.74*
CF/P	20.6%	4.8%	1.03%	-0.83	9.46	1.18	1.09	1.80
	18.1%	*6.2%*	*0.97%*	*-0.27*	*4.95*	*1.09*	*0.91*	*1.61*
E(Adj.)/EV	21.1%	5.4%	1.07%	-0.59	7.46	1.17	1.11	1.78
	18.2%	*6.4%*	*1.01%*	*-0.29*	*4.79*	*1.06*	*0.91*	*1.56*
E(Adj.)/P	19.4%	3.9%	1.07%	-0.62	7.29	1.07	1.01	1.61
	17.3%	*5.6%*	*1.02%*	*-0.20*	*4.57*	*0.98*	*0.86*	*1.45*
S/EV	17.4%	2.1%	1.09%	-0.65	11.35	0.94	0.91	1.38
	13.3%	*1.9%*	*1.01%*	*-0.09*	*4.33*	*0.75*	*0.65*	*1.05*
OPE+D&A/EV + M	19.7%	4.1%	1.03%	-0.90	11.09	1.13	1.05	1.73
	17.3%	*5.4%*	*0.96%*	*-0.34*	*5.81*	*1.05*	*0.88*	*1.56*
CF/EV + M	18.4%	2.9%	1.02%	-1.05	10.30	1.06	0.97	1.61
	15.2%	*3.6%*	*0.95%*	*-0.57*	*6.07*	*0.92*	*0.76*	*1.35*
CF/P + M	19.4%	3.8%	1.01%	-1.03	9.93	1.13	1.03	1.71
	16.2%	*4.5%*	*0.94%*	*-0.54*	*5.43*	*1.00*	*0.82*	*1.46*
E(Adj.)/EV + M	19.7%	4.0%	1.02%	-0.98	10.18	1.15	1.05	1.73
	16.8%	*5.0%*	*0.94%*	*-0.52*	*5.51*	*1.04*	*0.86*	*1.51*
E(Adj.)/P + M	19.3%	3.6%	1.00%	-0.95	9.41	1.14	1.05	1.71
	16.7%	*4.8%*	*0.93%*	*-0.51*	*5.25*	*1.04*	*0.86*	*1.52*
S/EV + M	15.6%	0.5%	1.04%	-0.77	12.48	0.87	0.82	1.30
	13.2%	*1.8%*	*0.98%*	*-0.11*	*6.35*	*0.76*	*0.65*	*1.11*
50/50 Mo_OPE+D&A/EV	24.0%	8.0%	1.02%	-1.01	11.47	1.41	1.30	2.17
	20.4%	*8.4%*	*0.95%*	*-0.40*	*5.85*	*1.27*	*1.06*	*1.90*
50/50 Mo_CF/EV	22.8%	7.0%	1.02%	-1.09	10.72	1.33	1.22	2.04
	19.1%	*7.3%*	*0.95%*	*-0.54*	*5.47*	*1.18*	*0.98*	*1.75*
50/50 Mo_CF/P	21.8%	6.1%	1.02%	-1.15	11.04	1.27	1.16	1.93
	18.5%	*6.8%*	*0.95%*	*-0.55*	*5.33*	*1.14*	*0.94*	*1.68*
50/50 Mo_E(Adj.)/EV	22.0%	6.3%	1.04%	-1.04	10.05	1.26	1.16	1.92
	18.6%	*6.8%*	*0.97%*	*-0.57*	*5.72*	*1.12*	*0.93*	*1.65*
50/50 Mo_E(Adj.)/P	21.2%	5.6%	1.04%	-1.00	9.95	1.21	1.11	1.82
	18.1%	*6.4%*	*0.98%*	*-0.50*	*5.55*	*1.08*	*0.91*	*1.59*
50/50 Mo_S/EV	20.0%	4.6%	1.03%	-0.97	12.69	1.15	1.08	1.74
	15.9%	*4.4%*	*0.96%*	*-0.32*	*5.69*	*0.96*	*0.81*	*1.40*

5.2.3 Performance of forward-looking sample strategies

In this section, returns for the forward-looking samples are reported. The main focus here is how forward-looking multiple portfolios compare to the corresponding past-looking multiple portfolios. It is important to note, that the samples are considerably smaller than in the main sample or momentum samples, so the equivalent multiple portfolios in different samples cannot be compared reliably to each other.

First, let's look at the market-adjusted returns. Table 15 reports the market-adjusted returns for the top 20 portfolios. In the top 20% portfolios all the portfolios had a positive market-adjusted (sample market) returns, except for *LTM_S/EV* (-2.1%) and *12F_S/EV* (-0.2%). Also, *LTM_E/P* (0.7%), *LTM_EBIT/EV* (0.2%) and *LTM_OPE/EV* (0.5%) had quite marginal market-adjusted returns. As can be seen in Table 15 the market-adjusted performance order for the forward-looking strategies is almost inverse compared to the past-looking strategies as *12F_EBITDA/EV* is behind *12F_E/EV* and *12F_EBIT*. As we can see, in all the multiple categories forward-looking multiples performs better than past-looking multiples. This especially evident with the multiples based on net income and EBIT. Here, the overlooked *12F_E/EV* is the top performer. This is not explained by the sample size as also with NTM_EBITDA sample it would be the top performer. Another interesting observation here is that the main sample top performer *LTM_OPE+D&A/EV* performs worse than non-operating adjusted *LTM_EBITDA/EV*. One possible explanation for this could be the fact that sometimes the companies which have analyst coverage in the Refinitiv Eikon database report the adjusted EBITDA and EBIT numbers which makes the operating adjustment less relevant.

Table 15 Summary of market-adjusted CAGRs for top 20% portfolios

	Market-adjusted CAGR
12F_E/EV	5.4%
12F_EBIT/EV	4.0%
12F_EBITDA/EV	3.3%
LTM_EBITDA/EV	3.0%
12F_E/P	2.5%
LTM OPE+D&A/EV	2.3%
LTM_E/EV	1.8%
LTM_E/P	0.7%
LTM_OPE/EV	0.5%
LTM_EBIT/EV	0.2%
12F_S/EV	-0.2%
LTM_S/EV	-2.1%

Table 16 Summary of forward-looking multiple improvement over market and past-looking multiple

Top 30%	CAGR	M-Ad. CAGR	Std. dev.	Sharpe	Sortino	Sortino_F
Market	4/5	4/5	0/5	4/5	4/5	4/5
Past-looking multiple	3/5	3/5	0/5	3/5	3/5	3/5
Top 20%						
Market	4/5	4/5	0/5	4/5	4/5	4/5
Past-looking multiple	5/5	5/5	0/5	4/5	4/5	4/5
Top 20						
Market	4/5	4/5	0/5	4/5	4/5	4/5
Past-looking multiple	4/5	5/5	1/5	4/5	4/5	4/5

Do the forward-looking multiples perform better than the past-looking multiples? Table 16 reports the summary of the improvement over the past-looking multiples and the technology sector. Only in the case of *12F_EBITDA/EV* the past-looking multiple performs better if we look at the risk-adjusted returns. *12F_EBITDA/EV* underperformance is quite marginal compared to the other multiples. Forward-looking multiples in general generate higher, but more volatile returns. Except for the *12F_EBITDA/EV,* the market-adjusted returns are significantly higher for the forward-looking multiples. The standard deviation is also higher, but it does not offset the high returns. As we can see from Table 15 the mean Sharpe ratio being 0.90 for the forward-looking multiples and 0.77 for the comparative past-looking multiples (16.7% higher). The story is same with the measures that consider only downside deviation: the mean Sortino ratio being 18.3% and Sortino_F ratio 17.3% higher. The outperformance is even stronger if we look at the pre-Covid values. These findings are contrary to the Gray and Vogel (2012) findings who found that forward-looking E/P performed poorly. The results are implying that investors give more weight for the forward-looking valuation metrics as the finance theory suggests. The outperformance of the forward-looking multiples over the past-looking multiples is quite strong.

Table 17 Risk-adjusted mean measures for the forward-looking and past-looking multiples

Top 20% portfolios	Sharpe	Sortino	Sortino_F
Mean past-looking	0.77	0.73	1.13
Mean forward-looking	0.90	0.86	1.33
Difference	***16.7%***	***18.3%***	***17.3%***
Pre-Covid mean past-looking	0.61	0.53	0.88
Pre-Covid mean forward-looking	0.74	0.65	1.07
Difference pre-Covid	***21.0%***	***23.2%***	***21.8%***

Table 18 Returns for the forward-looking samples

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current technology sector market portfolio. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the forward-looking samples overall technology sector. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios. Only Top 20% portfolios are reported here, Top 30%, and Top 20 portfolios are reported in the Appendix 3.

Top 20%	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F
Market (EBITDA)	13.1%	0.0%	0.94%	-1.15	11.47	0.80	0.72	1.20
	9.5%	*0.0%*	*0.87%*	*-0.63*	*6.35*	*0.59*	*0.48*	*0.85*
LTM_EBITDA/EV	16.8%	3.0%	1.01%	-0.76	9.81	0.97	0.92	1.44
	13.8%	*3.8%*	*0.94%*	*-0.27*	*5.12*	*0.83*	*0.71*	*1.20*
LTM OPE+D&A/EV	15.9%	2.3%	1.02%	-0.68	9.10	0.90	0.86	1.33
	12.5%	*2.6%*	*0.96%*	*-0.27*	*5.01*	*0.73*	*0.63*	*1.05*
12F_EBITDA/EV	17.0%	3.3%	1.07%	-0.59	9.41	0.93	0.90	1.37
	13.0%	*3.1%*	*1.01%*	*-0.11*	*4.91*	*0.73*	*0.64*	*1.05*
Market (EBIT)	12.5%	0.0%	0.94%	-1.17	11.47	0.76	0.68	1.14
	8.9%	*0.0%*	*0.87%*	*-0.65*	*6.29*	*0.55*	*0.44*	*0.80*
LTM_EBIT/EV	12.8%	0.2%	1.03%	-0.77	8.29	0.71	0.66	1.03
	10.3%	*1.2%*	*0.99%*	*-0.39*	*4.63*	*0.57*	*0.49*	*0.81*
LTM_OPE/EV	13.1%	0.5%	1.05%	-0.77	8.79	0.71	0.66	1.04
	10.6%	*1.5%*	*1.00%*	*-0.38*	*4.95*	*0.59*	*0.50*	*0.84*
12F_EBIT/EV	17.1%	4.0%	1.05%	-0.63	7.62	0.95	0.90	1.41
	13.9%	*4.5%*	*1.00%*	*-0.30*	*5.24*	*0.78*	*0.69*	*1.14*
Market (E)	13.2%	0.0%	0.93%	-1.30	12.72	0.81	0.72	1.23
	9.6%	*0.0%*	*0.86%*	*-0.70*	*6.55*	*0.61*	*0.48*	*0.88*
LTM_E/EV	15.4%	1.8%	1.06%	-0.70	7.36	0.84	0.78	1.24
	11.7%	*1.9%*	*1.01%*	*-0.37*	*4.89*	*0.65*	*0.56*	*0.94*
LTM_E/P	14.1%	0.7%	1.07%	-0.60	7.19	0.76	0.72	1.12
	11.0%	*1.3%*	*1.02%*	*-0.28*	*4.97*	*0.60*	*0.52*	*0.87*
12F_E/EV	19.4%	5.4%	1.09%	-0.64	7.26	1.05	0.99	1.56
	16.8%	*6.5%*	*1.04%*	*-0.29*	*4.64*	*0.93*	*0.82*	*1.37*
12F_E/P	16.2%	2.5%	1.07%	-0.67	8.01	0.89	0.84	1.31
	13.7%	*3.7%*	*1.02%*	*-0.23*	*4.35*	*0.77*	*0.67*	*1.10*
Market (S)	13.3%	0.0%	0.93%	-1.33	13.13	0.82	0.73	1.25
	9.8%	*0.0%*	*0.86%*	*-0.71*	*6.48*	*0.62*	*0.49*	*0.91*
LTM_S/EV	11.1%	-2.1%	1.08%	-0.87	9.75	0.58	0.55	0.81
	7.9%	*-1.8%*	*1.03%*	*-0.30*	*3.85*	*0.40*	*0.36*	*0.55*
12F_S/EV	13.3%	-0.2%	1.09%	-0.81	9.03	0.70	0.66	0.99
	9.5%	*-0.4%*	*1.03%*	*-0.33*	*3.67*	*0.50*	*0.44*	*0.68*

5.3 Risk-adjusted performance of the strategies

5.3.1 Main Sample

In this section, we examine whether the documented abnormally high returns in the *main sample* portfolios can be explained by a wider set of risk-adjustment methods. The purpose of this part of the analysis is to test whether these high returns can be explained by the market, size, or value factors. Table 19 reports abnormal returns for the top 20% portfolios studied in the main sample. The reported alphas are obtained from the Fama-French three-factor model.

As can be seen in Table 19, all the strategies yielded significant abnormal returns in the Nordic market setting. Interestingly all the strategies also yielded higher abnormal returns than the overall Nordic technology sector. All the alphas are statistically significant on at least 1% level for the whole observation period. For the pre-Covid period the story is pretty much the same. First, we have *OPE+D&A/EV* (18.66%) yielding almost double abnormal returns compared to the total technology sector (9.76%), but the *CF/EV* (18.45%) is right behind it. The third group 1 multiple *CF/P* with 17.30% also stands out from the rest. Next, we have *OPE+D&A/P* (15.40%), *E(Adj.)/EV* (15.26%), *EBITDA/EV* (15.22%), *OPE/EV* (14.82%). As can be seen the traditional book value multiples *B/P* (11.45%) and *B/EV* (12.22%) improve relatively speaking compared to other multiples being above *S/P* (10.40%), *D/P* (10.81%) and *EBIT/P* (11.44%).

Enterprise value-based multiples yielded higher abnormal returns than the comparative market capitalization-based multiples in all the classes. On average EV-based multiples yield economically significant 1.68% percentage points higher alphas. Again, the operating-adjusted multiples are superior to the non-adjusted multiples. Adjusted multiples yielding on average 1.78% percentage points higher abnormal returns compared to their comparative non-adjusted counterparts.

The evidence is quite clear here that the investors should give EV-based and operating-adjusted multiples higher weight in their decision-making if they are following value-investing strategies, at least in the technology sector. As can be seen in Table 19, the most studied multiples in the traditional value investing literature (*B/P, E/P, S/P, D/P*) perform quite poorly compared to the top performers. The multiples which are based on the operating cash flow (*OPE+D&A/EV* and *CF/EV*) seems to be the top performers in

Table 19 Abnormal returns and factor loadings for the main sample

The table reports abnormal returns, factor loadings and adjusted R squares for the top 20% portfolios in the main sample. The alphas are measured by Fama-French three factor model. The alphas are calculated from daily returns and annualized by raising to power of 252, assuming 252 trading days. In the grey background with italics are the pre-Covid results. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

Main sample top 20% portfolios	Alpha	MARKET	SIZE	VALUE	Adj. R Square
Main_Market	9.76%***	0.522***	0.394***	-0.041***	62.24%
Pre-Covid	7.37%***	0.489***	0.347***	-0.039**	60.54%
OPE+D&A/EV	18.66%***	0.494***	0.320***	0.037*	47.20%
	16.85%***	0.460***	0.256***	0.028	44.95%
CF/EV	18.45%***	0.504***	0.305***	0.038*	47.84%
	16.37%***	0.473***	0.249***	0.025	46.54%
CF/P	17.30%***	0.514***	0.313***	0.055***	51.31%
	15.87%***	0.483***	0.263***	0.026	48.47%
OPE+D&A/P	15.40%***	0.526***	0.314***	0.064***	52.53%
	13.84%***	0.497***	0.259***	0.054***	49.23%
E(Adj)/EV	15.26%***	0.540***	0.329***	-0.005	51.57%
	13.54%***	0.510***	0.271***	-0.014	49.29%
EBITDA/EV	15.22%***	0.505***	0.325***	0.048**	46.84%
	13.21%***	0.473***	0.269***	0.044**	44.68%
OPE/EV	14.82%***	0.512***	0.310***	0.011	50.83%
	13.22%***	0.483***	0.250***	-0.009	49.23%
EBITDA/P	14.45%***	0.516***	0.318***	0.058***	51.17%
	12.66%***	0.489***	0.267***	0.050**	47.79%
OPE/P	13.37%***	0.533***	0.335***	0.021	56.63%
	12.19%***	0.504***	0.279***	-0.006	53.50%
E(Adj.)/P	14.08%***	0.551***	0.335***	0.031	54.40%
	13.11%***	0.524***	0.283***	0.010	50.70%
EBIT/EV	13.33%***	0.510***	0.311***	0.015	50.52%
	11.78%***	0.481***	0.253***	-0.006	49.21%
E/P	12.97%***	0.543***	0.325***	0.044**	55.68%
	11.79%***	0.518***	0.277***	0.027	52.37%
S/EV	13.37%***	0.474***	0.379***	0.030	38.04%
	10.45%***	0.436***	0.331***	0.012	34.52%
EBIT/P	11.44%***	0.508***	0.312***	0.045**	54.13%
	10.31%***	0.480***	0.253***	0.024	51.12%
D/P	10.81%***	0.500***	0.313***	0.024	49.80%
	9.44%***	0.481***	0.285***	0.011	46.22%
B/EV	12.22%***	0.463***	0.336***	0.020	31.31%
	9.16%**	0.427***	0.298***	0.024	28.99%
B/P	11.45%***	0.472***	0.351***	0.030	33.16%
	7.50%*	0.437***	0.306***	0.026	30.12%
S/P	10.40%***	0.460***	0.376***	0.021	37.16%
	7.88%**	0.430***	0.322***	-0.004	34.78%

the technology sector. One explanation could be that the markets are undervaluing the payoff from the investments that the companies are making into tangible and especially intangible assets. The intangible assets that can be seen in the balance sheet, also are potentially amortized too fast compared to their real economic lifetime, which results in suppressed earnings below EBITDA and in this case the suppressed earnings do not reflect the firms' real earning power well. Interestingly, the most used multiple among the high growth technology sector, *S/EV,* also performs poorly compared to the earnings multiples, though it is good to remember that the sector is quite heterogenic

5.3.2 Momentum Sample

In this section, we examine whether the documented abnormally high returns in the *momentum sample* portfolios can be explained by a wider set of risk-adjustment methods. The purpose of this part of the analysis is to test whether these high returns can be explained by the market, size, or value factors. Table 20 reports abnormal returns for the top 20% portfolios studied in the momentum sample. The reported alphas are obtained from the Fama-French three-factor model. Here again, the focal point of our interest is whether the momentum composite portfolios can improve the sole value portfolios.

The momentum portfolio *mome_6-1m* yields itself significant abnormal returns (16.19%). And the value factor for it, is negative (-0.094) and statistically significant at 1% level. The three-factor alpha is higher than *CF/P* (15.14%), but lower than *OPE+D&A/EV* (19.90%) and *CF/EV* (17.36%). It is also higher than *E(Adj.)/EV* (15.41%), *E(Adj.)/P* (13.68%) and *S/EV* (12.65%).

The ranking scheme portfolios do not improve the alphas in any of the multiples. The results are similar to the other risk-adjusted measures that were used before where average ranking method improved only *E(Adj.)/P's* Sharpe, Sortino and Sortino_F ratios marginally. This is a little bit surprising that incorporating the higher yielding momentum does not improve even the worst performers *S/EV* and *E(Adj.)/P.* However, all the portfolios returned higher abnormal returns than the total technology sector (8.99%). The ranking scheme method could have probably improved the returns of the traditional *B/P* portfolio as Grobys and Huhta-Halkola (2019) found in the Nordic market with long-short portfolios, but there is really no point using the *B/P* strategy at all in the Nordic technology sector according to the evidence found in the main sample results. It is also important to note that Grobys and Huhta-Halkola observed that for the long-only portfolios returns diminished.

The 50/50 portfolios improve the abnormal returns in the portfolios in general when the multiples perform worse than the momentum portfolio. This is significant result because as reported in Table 14 the 50/50 portfolios are considerably less volatile. All the reported alphas are statistically significant at 1% level. The improvement in the alphas is largest in the *S/EV* and *E(Adj.)/P* portfolios. For the *OPE+D&A/EV* (18.00% vs. 19.90%) and *CF/EV* (16.79% vs. 17.36%) portfolios the effect is negative.

Incorporating the momentum in the value portfolios does not seem to improve the three-factor abnormal returns within the top performing multiples (*OPE+D&A/EV* and *CF/EV*) but it offers significant benefits for the other multiples. However, as we can be seen in Table 14 the other risk-adjusted measures Sharpe, Sortino and Sortino_F were improved also within the *50/50 CF/EV* portfolio. As Asness et al. (2013) found also (only for B/P strategy), it could be concluded that incorporating 50/50 momentum strategy does add value for the investors, as the outperformance of the *OPE+D&A/EV* multiple might be just linked to the chosen period and markets. Contrary to Grobys and Huhta-Halkola (2019) results, the 50/50 strategy seems to offer more benefits for the investors than the ranking scheme strategy.

Table 20 Three-factor alphas, factor loadings and adjusted R squares for the momentum sample in the top 20% portfolios

The table reports factor loadings for the Fama-French three factor model as well as the adjusted R squares for the regression analysis. The alphas are measured by Fama-French three factor model. The alphas are calculated from daily returns and annualized by raising to power of 252, assuming 252 trading days. *, ** and *** indicate statistical significance at 10%m 5% and 1% levels, respectively. All the multiples are top 20% portfolios in the momentum sample. Values with the grey background and italics are pre-Covid values for the measure in question. Precise t-values are not reported due the size constraints.

Momentum	Alpha	MARKET	SIZE	VALUE	Adj. R Squared
Mome_Market	8.99%***	0.528***	0.387***	-0.041***	62.27%
Pre-Covid	*6.44%****	*0.496****	*0.338****	*-0.038***	*60.61%*
Mome_6-1m	16.19%***	0.563***	0.431***	-0.094***	42.40%
	*13.61%****	*0.525****	*0.375****	*-0.073****	*38.82%*
OPE+D&A/EV	19.90%***	0.499***	0.307***	0.040*	46.05%
	*17.98%****	*0.465****	*0.242****	*0.034*	*43.90%*
CF/EV	17.36%***	0.515***	0.300***	0.035*	47.96%
	*15.12%****	*0.489****	*0.248****	*0.030*	*47.07%*
CF/P	15.14%***	0.523***	0.337***	0.042**	50.61%
	*13.69%****	*0.496****	*0.292****	*0.015*	*47.86%*
E(Adj.)/EV	15.41%***	0.547***	0.336***	-0.001	50.77%
	*13.74%****	*0.519****	*0.281****	*-0.015*	*48.49%*
E(Adj.)/P	13.68%***	0.559***	0.335***	0.028	53.57%
	*12.75%****	*0.534****	*0.283****	*0.008*	*49.92%*
S/EV	12.65%***	0.472***	0.371***	0.029	37.88%
	*9.71%****	*0.433****	*0.321****	*0.019*	*34.12%*
OPE+D&A/EV + M	13.94%***	0.534***	0.358***	-0.027	52.60%
	*12.86%****	*0.495****	*0.292****	*-0.017*	*48.74%*
CF/EV + M	12.52%***	0.544***	0.374***	-0.042**	55.38%
	*10.69%****	*0.508****	*0.311****	*-0.032*	*52.44%*
CF/P + M	13.48%***	0.545***	0.369***	-0.038**	56.18%
	*11.64%****	*0.509****	*0.308****	*-0.030*	*53.44%*
E(Adj.)/EV + M	13.84%***	0.521***	0.416***	-0.055***	51.51%
	*12.31%****	*0.479****	*0.354****	*-0.049***	*47.44%*
E(Adj.)/P + M	13.42%***	0.522***	0.403***	-0.050***	53.46%
	*12.11%****	*0.484****	*0.346****	*-0.048***	*49.82%*
S/EV + M	10.54%***	0.500***	0.364***	0.005	45.32%
	*9.27%****	*0.465****	*0.302****	*-0.007*	*41.20%*
50/50 Mo_OPE+D&A/EV	18.00%***	0.532***	0.368***	-0.028	52.90%
	*15.77%****	*0.496****	*0.306****	*-0.020*	*50.16%*
50/50 Mo_CF/EV	16.79%***	0.539***	0.365***	-0.032*	54.14%
	*14.41%****	*0.507****	*0.310****	*-0.024*	*51.89%*
50/50 Mo_CF/P	15.75%***	0.544***	0.384***	-0.031*	55.30%
	*13.75%****	*0.511****	*0.332****	*-0.032*	*52.60%*
50/50 Mo_E(Adj.)/EV	15.82%***	0.555***	0.384***	-0.050***	55.65%
	*13.72%****	*0.522****	*0.328****	*-0.046***	*52.98%*
50/50 Mo_E(Adj.)/P	15.00%***	0.562***	0.384***	-0.036**	56.63%
	*13.23%****	*0.530****	*0.330****	*-0.034**	*53.67%*
50/50 Mo_S/EV	14.31%***	0.520***	0.403***	-0.037*	49.57%
	*11.52%****	*0.481****	*0.349****	*-0.029*	*46.30%*

5.3.3 Forward-looking samples

In this section, we examine whether the documented abnormally high returns in the *forward-looking sample* portfolios can be explained by a wider set of risk-adjustment methods. The purpose of this part of the analysis is to test whether these high returns can be explained by the market, size, or value factors. Table 22 reports abnormal returns for the top 20% portfolios studied in the forward-looking sample. The reported alphas are obtained from the Fama-French three-factor model. In the forward-looking sample, the comparative performance of the forward-looking multiple against the past-looking multiple is in the focus. The forward-looking sample consists of more liquid larger companies which have analyst coverage.

The technology sector generated economically and statistically significant three-factor alpha also in the more liquid forward-looking sample. The market portfolios generated 6.44%–7.34% abnormal returns. The technology sector is correlated with *MARKET* and *SIZE* factors and negatively correlated with *VALUE* factor. Adjusted R squares are also higher in the forward-looking sample (69.77-71.47%) compared to the main (62.24%) and momentum samples (62.27%).

Table 21 Alpha spreads for the top 20% portfolios

The table reports alpha spreads for the top 20% portfolios in the forward-looking samples. The technology sector is equal to the respective multiple sample. Spread vs past-looking multiple is computed by comparing forward-looking multiple to the better performing past-looking multiple. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Alpha spread vs.	Technology sector	Past-looking multiple	Alpha
LTM_EBITDA/EV	4.28%		11.31%***
LTM OPE+D&A/EV	3.45%		10.48%***
12F_EBITDA/EV	**4.84%**	**0.56%**	**11.86%*** **
LTM_EBIT/EV	0.80%		7.24%***
LTM_OPE/EV	1.06%		7.50%***
12F_EBIT/EV	**5.19%**	**4.13%**	**11.63%*** **
LTM_E/EV	2.36%		9.59%***
LTM_E/P	1.12%		8.34%***
12F_E/EV	**6.52%**	**4.15%**	**13.75%*** **
12F_E/P	**3.58%**	**2.46%**	**10.81%*** **
LTM_S/EV	-0.98%		6.36%*
12F_S/EV	**1.07%**	**2.05%**	**8.41%** **

All the multiples generate higher abnormal returns than the technology sector except *LTM_S/EV* as can be seen in Table 21 which reports alpha spreads for the multiples. Only in the case of *12F_EBITDA/EV* it cannot be said that the forward-looking multiple improves clearly abnormal returns compared to the past-looking multiple. This could be linked to the documented outperformance of *OPE+D&A/EV* in the main and momentum samples. *12F_EBIT/EV* and *12F_E/EV* generate economically, and statistically very significant abnormal returns compared to their corresponding past-looking multiples (alpha spread 4.13% and 4.15% respectively) as well as compared to the technology sector (alpha spread 5.19% and 6.52% respectively). *12F_S/EV* and *12F_E/P* generate also economically, and statistically significant abnormal returns compared to their corresponding past-looking multiples (alpha spread 2.05% and 2.46% respectively) *12F_EBITDA/EV* also generated significant alpha compared to the technology sector (alpha spread 4.84%).

It can be concluded that the forward-looking value strategies are an improvement compared to the past-looking multiples. Among the studied forward-looking multiples, the forward-looking E/EV (*12F_E/EV)* was the strongest performer. This is interesting because in the past-looking samples (main and momentum) it was clearly behind *OPE+D&A/EV, CF/EV* and *CF/P*. Interestingly, it is also a clear improvement compared to the practitioners and academics favorite E/P ratio. When studying companies' valuations, investors might benefit from challenging the status quo, at least in the technology sector.

Table 22 Three-factor alphas, factor loadings and adjusted R squares for the forward-looking sample in the top 20% portfolios

The table reports factor loadings for the Fama-French three factor model as well as the adjusted R squares for the regression analysis. *, ** and *** indicate statistical significance at 10%m 5% and 1% levels, respectively. All the multiples are top 20% portfolios in the momentum sample. The alphas are measured by Fama-French three factor model. The alphas are calculated from daily returns and annualized by raising to power of 252, assuming 252 trading days. Values with the grey background and italics are pre-Covid values for the measure in question. Precise t-values are not reported due the size constraints.

Forward-looking	**Alpha**	**MARKET**	**SIZE**	**VALUE**	**Adj. R Squared**
Market_NTM_EBITDA	7.03%***	0.570***	0.392***	-0.051***	71.26%
Pre-Covid	*4.64%***	*0.543****	*0.348****	*-0.039****	*70.39%*
LTM_EBITDA/EV	11.31%***	0.548***	0.297***	0.038**	57.63%
	*9.50%****	*0.520****	*0.247****	*0.036**	*55.87%*
LTM OPE+D&A/EV	10.48%***	0.552***	0.295***	0.040**	56.79%
	*8.24%****	*0.522****	*0.245****	*0.033**	*54.85%*
12F_EBITDA/EV	11.86%***	0.530***	0.313***	0.071***	48.43%
	*9.02%****	*0.501****	*0.260****	*0.077****	*46.45%*
Market_NTM_EBIT	6.44%***	0.568***	0.392***	-0.052***	71.47%
	*4.12%***	*0.541****	*0.348****	*-0.040****	*70.61%*
LTM_EBIT/EV	7.24%***	0.583***	0.285***	0.009	61.75%
	*5.82%***	*0.564****	*0.239****	*-0.014*	*59.91%*
LTM_OPE/EV	7.50%***	0.591***	0.294***	0.029	61.14%
	*6.21%***	*0.567****	*0.242****	*0.009*	*58.78%*
12F_EBIT/EV	11.63%***	0.546***	0.335***	0.044**	52.90%
	*9.44%****	*0.527****	*0.302****	*0.032*	*50.82%*
Market_NTM_E(Adj.)	7.23%***	0.557***	0.398***	-0.042***	69.87%
	*4.83%***	*0.528****	*0.349****	*-0.035***	*69.00%*
LTM_E/EV	9.59%***	0.592***	0.308***	-0.001	59.57%
	*7.19%***	*0.567****	*0.256****	*-0.025*	*57.70%*
LTM_E/P	8.34%***	0.595***	0.332***	0.045**	61.12%
	*6.38%***	*0.575****	*0.289****	*0.036**	*59.04%*
12F_E/EV	13.75%***	0.544***	0.377***	0.024	49.06%
	*12.28%****	*0.521****	*0.332****	*0.025*	*46.33%*
12F_E/P	10.81%***	0.540***	0.372***	0.050**	50.94%
	*9.37%****	*0.520****	*0.324****	*0.036*	*48.13%*
Market_NTM_S	7.34%***	0.556***	0.399***	-0.044***	69.77%
	*5.04%***	*0.525****	*0.349****	*-0.037****	*69.00%*
LTM_S/EV	6.36%*	0.498***	0.380***	0.041*	42.89%
	4.19%	*0.472****	*0.329****	*0.017*	*39.22%*
12F_S/EV	8.41%**	0.501***	0.380***	0.030	42.30%
	5.71%	*0.477****	*0.332****	*0.022*	*39.44%*

5.4 Performance during bull and bear markets

5.4.1 Main sample

Similar to other studies (see e.g., Davydov et al. 2016; Grobys and Huhta-Halkola 2019), it is interesting to compare the performance of the value and combination strategies during the bull and bear markets separately. Davydov at al. (2016) argue that if the strategies involve taking additional risk, it should be expected to generate relatively lower risk-adjusted returns, especially during the market downturns. The bull and bear market periods are defined as an increase or decrease of 20% from the previous high (low) in the price of the FTSE Nordic All Cap Growth index. The increase or decrease must sustain itself above (below) 20% for at least 7 consecutive trading days to be regarded as a bull or bear market. Using this method, the observation period includes an aggregated 3364 days of bull market and 449 days of bear market. The aggregate bull period includes four separate bull markets and three separate bear market periods. Figure 14 presents the bull and bear markets as well as the corrections from the previous bull market high to the bear market low and vice versa.

Figure 14 Bull and Bear markets

FTSE Nordic All Cap GI. Reported percentages are the corrections from previous high to the low and vice versa. Ares with green background indicate bull market and areas with red background indicate bear market. Bull market is defined as more than 20% correction from the previous low and bear market as more than 20% correction from previous high. The correction must sustain itself as more than a 20% correction for at least 7 consecutive trading days to be considered as a bull or bear market.

Table 23 reports the bull market returns and performance measures as well as the three-factor alphas and factor loadings for the main sample top 20% portfolios. The main difference of the results is that the technology market-adjusted returns and three-factor alphas are higher compared to the total observation period for all the multiples except for *EBITDA/EV* and *B/EV*. *OPE+D&A/EV* and *CF/EV* are again the top multiples measured by raw returns, risk-adjusted returns and alphas, followed by *CF/P*. In the bull market setting the EV-based multiples outperform the market capitalization-based multiples, all though it is less clear now. Biggest difference compared to the total observation period is that *B/P* outperforms *B/EV* by a quite clear margin. Operating-adjusted ratios outperform clearly again the non-adjusted multiples. The pure-play value strategies seem to work exceptionally well during the bull market periods in the technology sector, but it is important to consider which multiples to apply as the spreads are quite large if we compare the top performers to the worst performers

Table 23 Main sample top 20% portfolios during the bull market periods

n = 3364. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BULL	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	19.9%	0.00%	1.15%	-0.39	3.76	1.017	0.941	1.428	0.95%**	0.989***	0.680***	0.016***	99.43%
Market	21.2%	0.00%	0.83%	-0.95	7.52	1.524	1.360	2.314	10.41%***	0.541***	0.351***	-0.029*	57.04%
OPE+D&A/EV	31.1%	7.75%	0.91%	-0.17	5.22	2.063	2.030	3.172	21.02%***	0.495***	0.258***	0.023	39.10%
CF/EV	31.1%	7.85%	0.91%	-0.26	5.08	2.061	1.989	3.166	20.96%***	0.497***	0.272***	0.007	39.14%
CF/P	30.0%	6.87%	0.89%	-0.36	4.85	2.029	1.945	3.116	19.78%***	0.504***	0.270***	0.033	42.19%
OPE+D&A/P	27.9%	5.18%	0.92%	-0.09	4.93	1.834	1.813	2.768	17.57%***	0.528***	0.265***	0.060***	44.23%
E(Adj)/EV	28.3%	5.57%	0.94%	-0.21	4.46	1.819	1.770	2.740	17.67%***	0.531***	0.285***	-0.029	42.12%
EBITDA/EV	26.3%	3.86%	0.94%	0.12	6.41	1.682	1.681	2.539	16.45%***	0.504***	0.277***	0.030	38.31%
OPE/EV	27.3%	4.63%	0.89%	-0.37	4.85	1.854	1.789	2.811	17.38%***	0.501***	0.251***	-0.013	41.94%
EBITDA/P	26.4%	3.96%	0.92%	0.04	5.61	1.731	1.705	2.600	16.25%***	0.521***	0.281***	0.059***	43.12%
OPE/P	26.8%	4.21%	0.88%	-0.43	4.67	1.837	1.761	2.780	16.15%***	0.538***	0.271***	0.018	49.76%
E(Adj.)/P	27.4%	4.86%	0.94%	-0.28	4.41	1.765	1.696	2.659	16.65%***	0.552***	0.275***	0.014	45.79%
EBIT/EV	24.9%	2.65%	0.90%	-0.03	5.99	1.665	1.635	2.533	14.97%***	0.507***	0.273***	0.000	42.29%
E/P	25.6%	3.30%	0.92%	-0.09	4.81	1.675	1.634	2.533	14.86%***	0.547***	0.301***	0.031	47.37%
S/EV	24.3%	2.23%	0.98%	-0.19	4.71	1.479	1.475	2.163	15.11%***	0.467***	0.323***	0.053**	31.01%
EBIT/P	23.7%	1.63%	0.86%	-0.12	5.80	1.648	1.604	2.467	13.84%***	0.511***	0.266***	0.035*	46.93%
D/P	22.0%	0.26%	0.89%	-0.39	4.22	1.469	1.477	2.323	12.64%***	0.492***	0.273***	0.005	40.09%
B/EV	21.3%	-0.13%	1.09%	0.02	3.63	1.163	1.213	1.644	12.77%***	0.469***	0.296***	0.057*	25.24%
B/P	23.0%	1.27%	1.06%	0.13	3.59	1.291	1.354	1.826	14.23%***	0.476***	0.296***	0.076***	27.31%
S/P	22.3%	0.59%	0.99%	0.01	4.59	1.345	1.367	1.958	13.24%***	0.475***	0.307***	0.033	31.21%

Table 24 reports the bear market returns and performance measures as well as the three-factor alphas and factor loadings for the main sample top 20% portfolios. The bear market results differ significantly compared to the total observation period and to the bull market results. Only 6/18 multiples can generate positive technology sector market-adjusted returns. The total technology sector performed exceptionally well during the bear market periods generating 5.24% alpha, all though not statistically significant. It also significantly outperformed Nordic Small Cap index. 14/18 multiples still generate positive three-factor alpha, but the abnormal returns are considerably lower than during the bull market setting. However, none of the alphas are statistically significant in the conventional levels. Interestingly, the worst performer of the bull market setting *B/EV* is the top performer during the bear markets measured by all the performance settings. Strikingly, *B/P* is among the worst performers. *B/EV* is followed by another underperformer during the bull market periods, *EBITDA/EV*. Third best performer was *OPE+D&A/EV* which seems to be the overall top performer. *CF/EV* and *CF/P* performed well during the bear markets as well. EV-based multiples outperformed the market capitalization-based multiples in all the instances. The outperformance is more evident than during the bull markets. Surprisingly, the non-operating adjusted multiples outperformed the adjusted multiples during the bear markets. Overall, the value strategies seem to perform better during the bull markets than during the bear markets, this is contrary to Pätäri et al. (2016) findings from the Finnish stock market.

Table 24 Main sample top 20% portfolios during the bear market periods

n = 449. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BEAR	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	-41.4%	0.00%	2.53%	-0.30	2.38	-0.171	-1.013	-0.132	0.51%	0.993***	0.709***	-0.011	99.62%
Market	-20.0%	0.00%	1.45%	-1.60	12.41	-0.049	-0.831	-0.034	5.24%	0.498***	0.467***	-0.052	75.30%
OPE+D&A/EV	-18.7%	1.67%	1.55%	-1.29	9.09	-0.049	-0.724	-0.034	6.83%	0.494***	0.435***	0.081*	68.36%
CF/EV	-20.0%	0.06%	1.60%	-1.14	7.83	-0.054	-0.753	-0.038	4.58%	0.508***	0.366***	0.118**	69.10%
CF/P	-20.7%	-0.59%	1.62%	-1.14	8.00	-0.056	-0.769	-0.039	5.07%	0.528***	0.397***	0.111**	72.12%
OPE+D&A/P	-21.7%	-2.03%	1.59%	-0.97	7.65	-0.058	-0.835	-0.041	3.52%	0.525***	0.403***	0.081*	73.17%
E(Adj)/EV	-23.1%	-3.53%	1.64%	-0.84	5.44	-0.063	-0.869	-0.045	3.00%	0.550***	0.413***	0.058	74.92%
EBITDA/EV	-16.2%	4.82%	1.59%	-1.46	10.52	-0.044	-0.617	-0.030	10.29%	0.506***	0.419***	0.101**	69.34%
OPE/EV	-22.4%	-2.74%	1.62%	-1.02	6.38	-0.061	-0.837	-0.043	3.33%	0.528***	0.427***	0.072	71.26%
EBITDA/P	-20.8%	-0.97%	1.55%	-1.18	8.45	-0.054	-0.800	-0.038	3.78%	0.511***	0.384***	0.064	71.96%
OPE/P	-26.5%	-7.93%	1.60%	-0.94	6.97	-0.070	-1.008	-0.051	-1.73%	0.529***	0.453***	0.042	72.47%
E(Adj.)/P	-25.4%	-6.51%	1.63%	-0.85	5.62	-0.069	-0.949	-0.050	0.38%	0.549***	0.445***	0.085**	75.89%
EBIT/EV	-20.0%	0.17%	1.58%	-1.46	10.00	-0.053	-0.760	-0.037	5.08%	0.516***	0.384***	0.054	70.09%
E/P	-23.8%	-4.65%	1.58%	-1.08	7.03	-0.063	-0.890	-0.046	0.42%	0.534***	0.363***	0.085**	76.18%
S/EV	-19.4%	0.97%	1.67%	-1.09	11.24	-0.055	-0.737	-0.038	7.25%	0.494***	0.491***	-0.036	56.23%
EBIT/P	-25.5%	-6.94%	1.55%	-1.36	9.58	-0.066	-0.948	-0.047	-2.43%	0.503***	0.395***	0.077*	70.62%
D/P	-22.1%	-2.71%	1.53%	-0.90	5.23	-0.057	-0.885	-0.042	2.15%	0.511***	0.392***	0.072*	74.59%
B/EV	-14.3%	7.03%	1.62%	-0.76	8.84	-0.040	-0.591	-0.028	11.04%	0.466***	0.411***	-0.071	51.74%
B/P	-26.6%	-8.19%	1.68%	-0.83	8.52	-0.074	-0.989	-0.055	-3.30%	0.479***	0.453***	-0.085	50.75%
S/P	-28.2%	-10.42%	1.53%	-1.90	14.98	-0.071	-1.037	-0.052	-6.24%	0.443***	0.493***	0.010	56.13%

5.4.2 Momentum sample

Table 25 reports the bull market returns and performance measures as well as the three-factor alphas and factor loadings for the momentum sample top 20% portfolios. Momentum portfolio performs worse if we look at the risk-adjusted measures compared to the total observation period relative to the pure-play value strategies. Again, the ranking scheme portfolios do not improve the value strategies. 50/50 strategies improve clearly only the worst performing strategies *S/EV* and *E(Adj.)/P*. The ranking scheme method does decrease the volatility of the portfolios more than the 50/50 strategies, but both strategies tilt the returns towards unfavorable more asymmetric distributions. These results are contrary to the Leivo (2012) results from the Finnish stock market. Momentum does not seem to improve the pure-play value portfolios during the bullish market periods in the Nordic stock market.

Table 25 Momentum sample top 20% portfolios during the bull market periods

n = 3364. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BULL	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	19.9%	0.00%	1.15%	-0.39	3.76	1.017	0.941	1.428	0.95%**	0.989***	0.680***	0.016***	99.43%
Market_Mome	20.5%	0.00%	0.84%	-0.90	7.37	1.455	1.325	2.193	9.74%***	0.547***	0.345***	-0.031*	56.85%
Mome_6-1m	28.2%	6.53%	1.14%	-0.24	6.31	1.494	1.472	2.233	15.95%***	0.611***	0.399***	-0.096***	38.34%
OPE+D&A/EV	32.3%	9.36%	0.93%	-0.10	5.23	2.104	2.072	3.246	21.02%***	0.495***	0.258***	0.023	39.10%
CF/EV	29.7%	7.27%	0.93%	-0.16	4.98	1.932	1.892	2.940	20.96%***	0.497***	0.272***	0.007	39.14%
P/CF	28.3%	6.09%	0.91%	-0.27	4.61	1.869	1.789	2.832	18.17%***	0.512***	0.270***	0.035	41.71%
E(Adj.)/EV	28.5%	6.30%	0.95%	-0.19	4.80	1.799	1.758	2.725	17.89%***	0.532***	0.280***	-0.031	40.74%
E(Adj.)/P	26.9%	4.99%	0.96%	-0.25	4.61	1.681	1.624	2.529	16.65%***	0.552***	0.275***	0.014	45.79%
S/EV	23.1%	1.80%	0.97%	-0.20	5.01	1.418	1.410	2.056	15.11%***	0.467***	0.323***	0.053**	31.01%
OPE+D&A/EV + M	26.5%	4.67%	0.91%	-0.39	5.00	1.755	1.690	2.634	15.90%***	0.532***	0.298***	-0.036*	45.14%
CF/EV + M	24.6%	3.08%	0.89%	-0.67	4.80	1.661	1.560	2.469	13.89%***	0.531***	0.329***	-0.053***	47.41%
CF/P + M	26.0%	4.19%	0.89%	-0.65	4.49	1.753	1.641	2.609	14.99%***	0.542***	0.321***	-0.044**	49.06%
E(Adj.)/EV + M	25.3%	3.69%	0.92%	-0.58	5.29	1.644	1.545	2.438	14.32%***	0.542***	0.342***	-0.054**	45.80%
E(Adj.)/P + M	25.3%	3.66%	0.90%	-0.58	5.07	1.681	1.575	2.495	14.37%***	0.542***	0.328***	-0.051**	47.64%
S/EV + M	21.4%	0.39%	0.95%	-0.11	6.52	1.336	1.301	1.968	11.81%***	0.514***	0.277***	0.029	38.87%
50/50 Mo_OPE+D&A/E	30.6%	8.25%	0.93%	-0.51	6.55	1.998	1.907	3.073	19.05%***	0.553***	0.323***	-0.038*	47.19%
50/50 Mo_CF/EV	29.4%	7.27%	0.92%	-0.63	5.89	1.922	1.816	2.935	17.86%***	0.555***	0.332***	-0.045**	47.87%
50/50 Mo_CF/P	28.8%	6.73%	0.92%	-0.67	5.72	1.885	1.768	2.861	17.13%***	0.564***	0.334***	-0.035*	49.68%
50/50 Mo_E(Adj.)/EV	28.8%	6.77%	0.94%	-0.64	6.09	1.853	1.740	2.801	16.93%***	0.573***	0.339***	-0.066***	49.40%
50/50 Mo_E(Adj.)/P	28.0%	6.15%	0.95%	-0.61	6.08	1.783	1.685	2.686	16.03%***	0.589***	0.338***	-0.048**	51.10%
50/50 Mo_S/EV	25.9%	4.41%	0.94%	-0.47	6.67	1.654	1.589	2.490	14.86%***	0.541***	0.361***	-0.025	44.32%

Table 26 reports the bear market returns and performance measures as well as the three-factor alphas and factor loadings for the momentum sample top 20% portfolios. During the bear market periods, pure momentum strategy clearly outperforms the overall technology sector, producing 7.16% market-adjusted annual return. The high returns are not offset by higher volatility as during the bull market periods. The momentum clearly generated higher risk-adjusted returns than the technology sector as well. Ranking scheme strategy has great divergence between multiples in improvement. It worsens the performance of *OPE+D&A* multiples and significantly improves the *E(Adj.)* multiples. In fact, *E(Adj.)/EV + M* is the top performing strategy even though pure *E(Adj.)/EV* was the third worst performer. The ranking scheme improvement is not very clear because of the differences between the improvement of the strategies. 50/50 strategies improve all the pure-play value portfolios, but none of them improve the pure-play momentum strategy. All strategies generate positive alpha but none of them are statistically significant despite this the combination momentum strategies improve the portfolios more during the bear market periods.

Table 26 Momentum sample top 20% portfolios during the bear market periods

n = 449. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BEAR	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	-41.4%	0.00%	2.53%	-0.30	2.38	-0.171	-1.013	-0.132	0.51%	0.993***	0.709***	-0.011	99.62%
Market_Mome	-21.3%	0.00%	1.46%	-1.56	12.25	-0.052	-0.881	-0.036	3.68%	0.505***	0.457***	-0.046	75.88%
Mome_6-1m	-15.6%	7.16%	1.60%	-1.47	10.57	-0.043	-0.606	-0.030	11.18%	0.489***	0.462***	-0.042	59.55%
OPE+D&A/EV	-17.3%	5.09%	1.59%	-1.16	8.34	-0.047	-0.673	-0.032	6.83%	0.494***	0.435***	0.081*	68.36%
CF/EV	-19.5%	2.52%	1.65%	-1.04	6.63	-0.054	-0.717	-0.038	4.58%	0.508***	0.366***	0.118**	69.10%
CF/P	-24.8%	-4.14%	1.66%	-1.12	7.10	-0.069	-0.886	-0.049	1.60%	0.544***	0.469***	0.056	71.10%
E(Adj.)/EV	-22.8%	-1.54%	1.69%	-0.81	5.00	-0.064	-0.833	-0.046	4.79%	0.568***	0.449***	0.070	75.23%
E(Adj.)/P	-24.9%	-4.37%	1.65%	-0.85	5.40	-0.069	-0.930	-0.050	0.38%	0.549***	0.445***	0.085**	75.89%
S/EV	-18.2%	4.14%	1.70%	-0.98	10.47	-0.053	-0.682	-0.036	7.25%	0.494***	0.491***	-0.036	56.23%
OPE+D&A/EV + M	-21.9%	-0.52%	1.65%	-1.14	8.97	-0.061	-0.808	-0.041	5.26%	0.541***	0.474***	-0.001	69.68%
CF/EV + M	-20.1%	2.02%	1.69%	-1.02	7.07	-0.057	-0.713	-0.040	8.70%	0.566***	0.468***	-0.018	71.91%
CF/P + M	-20.6%	1.23%	1.65%	-1.04	7.37	-0.057	-0.761	-0.039	7.23%	0.552***	0.463***	-0.021	71.56%
E(Adj.)/EV + M	-15.9%	6.70%	1.53%	-1.32	10.04	-0.042	-0.640	-0.028	12.42%	0.494***	0.549***	-0.032	68.29%
E(Adj.)/P + M	-18.4%	3.48%	1.52%	-1.18	8.62	-0.047	-0.745	-0.032	8.93%	0.497***	0.536***	-0.024	70.03%
S/EV + M	-20.2%	1.31%	1.56%	-1.60	12.79	-0.053	-0.760	-0.035	6.32%	0.492***	0.525***	-0.041	64.44%
50/50 Mo_OPE+D&A/E	-16.5%	6.13%	1.54%	-1.48	10.75	-0.043	-0.653	-0.030	9.76%	0.499***	0.437***	0.023	68.78%
50/50 Mo_CF/EV	-17.5%	4.86%	1.56%	-1.44	9.69	-0.047	-0.686	-0.032	8.61%	0.514***	0.415***	0.019	70.54%
50/50 Mo_CF/P	-20.2%	1.55%	1.57%	-1.47	10.01	-0.053	-0.772	-0.037	6.20%	0.515***	0.466***	0.004	70.07%
50/50 Mo_E(Adj.)/EV	-19.1%	2.97%	1.58%	-1.28	8.49	-0.051	-0.733	-0.036	7.93%	0.528***	0.457***	0.012	72.28%
50/50 Mo_E(Adj.)/P	-20.2%	1.51%	1.57%	-1.30	8.90	-0.053	-0.781	-0.037	6.13%	0.520***	0.455***	0.023	72.49%
50/50 Mo_S/EV	-16.6%	6.13%	1.56%	-1.47	12.76	-0.044	-0.668	-0.030	10.14%	0.494***	0.472***	-0.046	64.06%

5.4.3 Forward-looking samples

Table 27 reports the bull market returns and performance measures as well as the three-factor alphas and factor loadings for the forward-looking samples' top 20% portfolios. During the bull market periods, all the strategies generate positive market-adjusted returns, except *LTM_S/EV*. All the strategies also generate positive and statistically significant three-factor alpha. Forward-looking portfolios outperform the past-looking portfolios except in the case of *LTM_EBITDA/EV* and *LTM_OPE+D&A/EV* which are also the best performing past-looking multiples. However, for the other strategies the improvement is significant which does seem to imply that the forward-looking strategies work better during the bull market periods.

Table 27 Forward-looking samples top 20% portfolios during the bull market periods

n = 3364. * , ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BULL	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	19.9%	0.00%	1.15%	-0.39	3.76	1.017	0.941	1.428	0.95%**	0.989***	0.680***	0.016***	99.43%
Market (EBITDA)	18.3%	0.00%	0.84%	-0.79	6.61	1.286	1.170	1.910	6.84%***	0.598***	0.348***	-0.045***	67.61%
LTM_EBITDA/EV	23.1%	3.81%	0.90%	-0.32	5.26	1.537	1.501	2.268	12.68%***	0.556***	0.251***	0.031	50.60%
LTM OPE+D&A/EV	22.7%	3.48%	0.91%	-0.32	5.33	1.478	1.442	2.170	12.28%***	0.562***	0.245***	0.043**	49.86%
12F_EBITDA/EV	21.7%	2.69%	0.94%	-0.17	4.35	1.369	1.362	1.989	12.21%***	0.520***	0.253***	0.067***	40.34%
Market (EBIT)	17.6%	0.00%	0.83%	-0.81	6.51	1.245	1.128	1.839	6.27%***	0.595***	0.349***	-0.048***	67.84%
LTM_EBIT/EV	18.5%	0.55%	0.90%	-0.40	4.26	1.204	1.139	1.729	7.99%***	0.584***	0.258***	0.008	54.57%
LTM_OPE/EV	19.8%	1.71%	0.91%	-0.44	4.50	1.285	1.226	1.859	9.37%***	0.586***	0.233***	0.020	53.98%
12F_EBIT/EV	22.2%	3.66%	0.93%	-0.46	4.81	1.424	1.373	2.085	11.91%***	0.540***	0.293***	0.039*	45.26%
Market (E)	18.8%	0.00%	0.82%	-0.88	6.95	1.344	1.204	2.015	7.55%***	0.578***	0.349***	-0.036**	65.51%
LTM_E/EV	22.1%	2.71%	0.93%	-0.44	4.46	1.413	1.344	2.073	11.27%***	0.582***	0.275***	-0.012	51.00%
LTM_E/P	21.3%	2.05%	0.94%	-0.34	4.40	1.355	1.300	1.986	10.35%***	0.595***	0.284***	0.028	53.30%
12F_E/EV	25.8%	5.81%	0.95%	-0.40	4.13	1.635	1.591	2.411	15.49%***	0.516***	0.327***	0.005	39.69%
12F_E/P	23.2%	3.53%	0.93%	-0.44	4.27	1.493	1.444	2.190	13.02%***	0.524***	0.316***	0.046**	42.87%
Market (S)	18.8%	0.00%	0.82%	-0.91	7.03	1.346	1.207	2.019	7.56%***	0.577***	0.353***	-0.038**	65.43%
LTM_S/EV	18.5%	-0.38%	0.98%	-0.25	3.66	1.116	1.111	1.557	9.28%***	0.503***	0.313***	0.065***	36.20%
12F_S/EV	20.1%	0.98%	0.97%	-0.28	3.43	1.223	1.205	1.715	10.80%***	0.494***	0.330***	0.053**	35.09%

Table 28 reports the bear market returns and performance measures as well as the three-factor alphas and factor loadings for the forward-looking samples' top 20% portfolios. During the bear market periods, only 3/12 of the strategies generated positive market-adjusted returns. All of them are forward-looking strategies. 7/12 of the strategies generate positive and but not statistically significant three-factor alpha. The technology sector performs exceptionally well during the bear market periods. The best performing strategy is the *12F_EBITDA/EV* which is coherent with the results from the main sample. All the forward-looking strategies outperform their past-looking counterparts. It is generally thought that the investors perspective shortens during the bear markets, and they appreciate more the actualized results. However, the results imply that the counterstrategy to this behavior would the most profitable one.

Table 28 Forward-looking samples top 20% portfolios during the bear market periods

n = 449. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Precise t-values are not reported due the size constraints.

BEAR	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	Alpha	MARKET	SIZE	VALUE	Adj. R Sqr.
Nordic Small Cap	-41.4%	0.00%	2.53%	-0.30	2.38	-0.171	-1.013	-0.132	0.51%	0.993***	0.709***	-0.011	99.62%
Market (EBITDA)	-19.6%	0.00%	1.50%	-1.20	8.73	-0.050	-0.804	-0.035	7.07%	0.533***	0.462***	-0.038	80.76%
LTM_EBITDA/EV	-21.8%	-2.67%	1.61%	-0.98	7.45	-0.059	-0.834	-0.042	3.55%	0.538***	0.381***	0.068	73.95%
LTM OPE+D&A/EV	-24.8%	-20.24%	1.61%	-0.82	6.90	-0.067	-0.957	-0.049	-0.28%	0.540***	0.382***	0.045	73.49%
12F_EBITDA/EV	-13.6%	7.97%	1.75%	-0.83	7.01	-0.041	-0.518	-0.029	16.63%	0.552***	0.439***	0.076	66.38%
Market (EBIT)	-20.1%	0.00%	1.50%	-1.20	8.66	-0.051	-0.826	-0.035	6.46%	0.532***	0.462***	-0.036	80.74%
LTM_EBIT/EV	-22.6%	-2.77%	1.70%	-0.84	5.45	-0.064	-0.844	-0.046	3.63%	0.584***	0.336***	0.016	76.76%
LTM_OPE/EV	-27.4%	-8.55%	1.77%	-0.72	5.27	-0.081	-0.968	-0.059	-0.50%	0.601***	0.411***	0.055	75.56%
12F_EBIT/EV	-15.1%	6.52%	1.73%	-0.55	4.55	-0.045	-0.575	-0.032	14.40%	0.560***	0.422***	0.055	69.34%
Market (E)	-21.4%	0.00%	1.50%	-1.34	9.53	-0.054	-0.866	-0.038	5.09%	0.531***	0.480***	-0.037	80.28%
LTM_E/EV	-25.4%	-4.54%	1.76%	-0.63	4.25	-0.074	-0.914	-0.054	1.67%	0.606***	0.375***	0.025	77.52%
LTM_E/P	-28.7%	-8.92%	1.74%	-0.55	4.25	-0.083	-1.041	-0.061	-2.43%	0.595***	0.422***	0.096**	78.06%
12F_E/EV	-20.2%	2.10%	1.83%	-0.56	4.00	-0.062	-0.699	-0.045	10.54%	0.589***	0.490***	0.056	68.42%
12F_E/P	-25.3%	-4.55%	1.78%	-0.55	4.82	-0.075	-0.912	-0.056	2.63%	0.569***	0.488***	0.053	67.47%
Market (S)	-20.7%	0.00%	1.49%	-1.39	10.11	-0.052	-0.847	-0.036	5.72%	0.529***	0.476***	-0.037	80.23%
LTM_S/EV	-32.1%	-14.32%	1.63%	-1.49	10.38	-0.086	-1.157	-0.064	-9.08%	0.499***	0.503***	-0.011	60.84%
12F_S/EV	-27.8%	-8.69%	1.70%	-1.21	8.41	-0.078	-0.983	-0.058	-2.88%	0.520***	0.480***	-0.034	59.80%

6 CONCLUSIONS

The main objective of this research was to determine which value investing strategies perform the best in the Nordic technology sector measured by raw and risk-adjusted returns. To gain more insight, additional research objectives were to test whether incorporating momentum can improve the pure-play value investing strategies, investigate whether enterprise value-based multiples outperform market capitalization-based multiples, to examine whether forward-looking multiples outperform past-looking multiples, and to investigate whether using operating-adjusted multiples is more profitable than using non-adjusted multiples. The research objectives were answered by studying a broad set of different value investing strategies in the Nordic technology sector from the 31st of March 2006 to the 1st of April 2021. Three different main samples were studied to gain more insight into the different research objectives: a *main sample*, a *momentum sample*, and *forward-looking samples*. Performance of the strategies during the bull and bear markets was also studied.

Between all the investigated past-looking multiples, the best value strategy was *OPE+D&A/EV* (operating-adjusted *EV/EBITDA*) measured by raw returns as well as by risk-adjusted returns. The *OPE+D&A/EV* top quintile portfolio generated 24.0% CAGR, 7.0% annual technology sector market-adjusted return and 18.7% three-factor alpha. It performed best during the bull markets and was also the third best performing multiple during the bear markets. Two other multiples that stood out from the rest were *CF/EV* and *CF/P,* especially *CF/EV*. They performed almost as well as *OPE+D&A/EV* during the bull markets but worse during the bear market periods. The results suggest that the multiples closest to the firms' cash flow from operations would perform best in the technology sector. Neither of these multiples consider depreciation and amortization as expenses, and the superb performance of these multiples over EBIT and net income multiples might suggest that depreciation and amortization are being depreciated too aggressively. The Nordic technology sector overall performed exceptionally well during the study period, generating an annual return of 15.5% and 9.76% three-factor alpha. The traditional value premium multiple *B/P* is among the worst performing multiples, and it clearly underperformed against the overall technology sector, which suggests that the accounting book value does not capture the value creation sufficiently in the technology sector. Sales based multiples *S/EV* and *S/P* performed quite poorly, especially *S/P*.

Momentum anomaly is also present in the Nordic technology sector and the pure-play buy-and-hold momentum strategy outperformed the technology sector. Value investors in the technology sector seem to gain additional benefit from incorporating momentum. Contrary to the results of Grobys and Huhta-Halkola (2019), between the two combination momentum strategies studied (50/50 and ranking scheme), 50/50 strategy was clearly superior. The 50/50 top quintile combination portfolios outperformed the pure-play value strategy, except in the case of *OPE+D&A/EV*. The 50/50 combination portfolios significantly reduce the volatility in most cases. However, incorporating momentum tilts the return distributions in an unfavorable direction. Interestingly, momentum improves the portfolios more during the bear market periods, but only a limited amount during the bull market periods.

Enterprise value-based multiples clearly outperform the market capitalization-based values. The outperformance is especially evident during the bear market periods. In all the cases, EV-based multiples outperformed their market capitalization-based counterpart. This is contrary to the Scheiner's (2007) results, who studied the value relevance of the multiples. The outperformance also applies to the never before studied multiples like *E/EV* and *B/EV*. The results suggest that investors should always consider the leverage of the firm in the technology sector.

Contrary to Gray's and Vogel's (2012) results, forward-looking multiples outperformed the past-looking multiples. The forward-looking samples were composed of larger companies with analyst coverage. Only *12F_EBITDA/EV* did not outperform its past-looking counterpart. Other forward-looking top quintile portfolios *12F_EBIT/EV, 12F_E/EV, 12F_E/P* and *12F_S/EV* outperformed significantly their past-looking counterparts. All the forward-looking portfolios exhibited higher volatility but generated significantly higher returns as well. Interestingly, *12F_E/EV* seems to be the top performer, followed by *12F_EBIT/EV. 12F_E/EV* significantly outperforms the most used multiple by practitioners, *12F_E/P. 12F_E/EV* is never explicitly used by the analysts because it is thought not to be coherent with finance theory. No prior academic research could be found that studied E/EV-multiples using the portfolio method. In fact, the great performance might be linked to the fact that everyone is over-looking this multiple.

Operating-adjusted multiples outperformed their non-adjusted counterparts in almost all the cases. The outperformance was less evident in the forward-looking samples. As a conclusion from these results, it is easier to navigate towards Lakonishok et al. (1994) explanation for the superior results for the value investing strategies which argue that the higher returns are not generated by carrying higher risk but because the strategies exploit the suboptimal behavior of the average investor.

The results of this research have many practical applicable use cases for the technology sector investors, especially for the smaller investors. However, it is good to note that the Nordic technology sector consists of many very small companies which do not have analyst coverage. In future research, it would be interesting to investigate the performance of the multiples which incorporate research & development expenses and gross profit metrics. These multiples were excluded from the study because of the data limitations. The US technology sector could be a fruitful research target because of the mature state of the sector, it consists of many large companies, and there would be a great amount of high-quality data available.

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APPENDIX

Appendix 1. Returns for the main sample

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current sample market. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the main sample market. The multiples are ranked according to the Top 20% -portfolios Sortino ratio. Except market returns are reported first. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios.

	Top30%							
	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F
Market	15.5%	0.0%	0.92%	-1.42	14.30	0.98	0.86	1.49
	11.9%	*0.0%*	*0.85%*	*-0.70*	*6.40*	*0.78*	*0.62*	*1.16*
OPE+D&A/EV	20.2%	3.7%	0.94%	-1.06	11.76	1.27	1.16	1.99
	17.5%	*4.7%*	*0.87%*	*-0.42*	*5.36*	*1.17*	*0.95*	*1.77*
CF/EV	21.8%	5.1%	0.96%	-1.05	10.90	1.35	1.22	2.10
	19.0%	*6.1%*	*0.89%*	*-0.47*	*4.82*	*1.26*	*1.02*	*1.89*
CF/P	21.1%	4.6%	0.96%	-1.12	11.39	1.31	1.17	2.05
	18.6%	*5.7%*	*0.90%*	*-0.51*	*5.63*	*1.22*	*0.98*	*1.84*
OPE+D&A/P	19.7%	3.3%	0.93%	-0.99	10.73	1.25	1.14	1.93
	17.6%	*4.7%*	*0.87%*	*-0.36*	*5.13*	*1.17*	*0.97*	*1.75*
E(Adj)/EV	19.9%	3.5%	0.96%	-0.89	8.42	1.23	1.11	1.87
	17.1%	*4.4%*	*0.90%*	*-0.53*	*5.28*	*1.10*	*0.91*	*1.64*
EBITDA/EV	19.7%	3.3%	0.94%	-1.06	12.24	1.24	1.13	1.90
	17.1%	*4.3%*	*0.87%*	*-0.35*	*4.87*	*1.13*	*0.94*	*1.69*
OPE/EV	19.4%	3.1%	0.95%	-0.98	9.71	1.20	1.09	1.85
	16.6%	*4.0%*	*0.89%*	*-0.49*	*5.11*	*1.08*	*0.89*	*1.62*
EBITDA/P	19.6%	3.3%	0.94%	-1.01	11.76	1.23	1.12	1.90
	17.1%	*4.3%*	*0.88%*	*-0.29*	*4.92*	*1.12*	*0.93*	*1.68*
OPE/P	18.9%	2.6%	0.94%	-0.96	9.54	1.18	1.07	1.81
	16.6%	*3.9%*	*0.89%*	*-0.44*	*4.96*	*1.08*	*0.89*	*1.62*
E(Adj.)/P	18.3%	2.1%	0.97%	-0.82	7.86	1.11	1.01	1.69
	15.9%	*3.3%*	*0.92%*	*-0.43*	*4.80*	*1.00*	*0.83*	*1.48*
EBIT/EV	19.1%	2.8%	0.94%	-0.97	10.41	1.20	1.09	1.84
	16.2%	*3.5%*	*0.88%*	*-0.42*	*5.01*	*1.06*	*0.87*	*1.58*
E/P	18.3%	2.2%	0.95%	-0.89	8.76	1.14	1.03	1.72
	16.0%	*3.4%*	*0.90%*	*-0.41*	*4.62*	*1.03*	*0.86*	*1.53*
S/EV	17.7%	1.6%	0.98%	-0.93	12.35	1.05	0.99	1.58
	13.6%	*1.3%*	*0.91%*	*-0.25*	*4.25*	*0.85*	*0.72*	*1.22*
EBIT/P	17.4%	1.3%	0.93%	-0.97	10.06	1.09	0.98	1.66
	14.9%	*2.4%*	*0.88%*	*-0.40*	*4.96*	*0.97*	*0.80*	*1.45*
D/P	17.0%	0.9%	0.91%	-1.01	9.57	1.09	1.00	1.68
	14.6%	*2.0%*	*0.86%*	*-0.51*	*4.94*	*0.97*	*0.82*	*1.46*
B/EV	15.1%	-0.5%	1.05%	-0.59	8.83	0.83	0.81	1.20
	11.3%	*-0.7%*	*0.98%*	*-0.12*	*3.87*	*0.64*	*0.56*	*0.89*
B/P	14.2%	-1.3%	1.05%	-0.63	9.45	0.78	0.76	1.13
	10.2%	*-1.6%*	*0.98%*	*-0.11*	*3.50*	*0.58*	*0.50*	*0.80*
S/P	15.2%	-0.5%	0.99%	-0.91	10.67	0.89	0.84	1.30
	11.7%	*-0.4%*	*0.93%*	*-0.27*	*4.01*	*0.70*	*0.60*	*0.99*

	Top20%							
	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F
Market	15.5%	0.0%	0.92%	-1.42	14.30	0.98	0.86	1.49
	11.9%	*0.0%*	*0.85%*	*-0.70*	*6.40*	*0.78*	*0.62*	*1.16*
OPE+D&A/EV	24.0%	7.0%	1.01%	-0.75	10.08	1.42	1.34	2.19
	21.0%	*7.8%*	*0.93%*	*-0.19*	*4.65*	*1.33*	*1.12*	*1.98*
CF/EV	23.8%	6.9%	1.02%	-0.77	9.55	1.39	1.29	2.14
	20.6%	*7.5%*	*0.94%*	*-0.30*	*4.47*	*1.29*	*1.07*	*1.91*
CF/P	22.8%	6.0%	1.01%	-0.88	10.22	1.35	1.24	2.08
	20.2%	*7.1%*	*0.94%*	*-0.26*	*4.70*	*1.26*	*1.06*	*1.89*
OPE+D&A/P	20.8%	4.3%	1.02%	-0.58	9.16	1.21	1.15	1.83
	18.1%	*5.3%*	*0.97%*	*0.02*	*4.79*	*1.10*	*0.96*	*1.62*
E(Adj)/EV	20.9%	4.5%	1.05%	-0.61	7.41	1.19	1.12	1.79
	18.0%	*5.2%*	*0.98%*	*-0.27*	*4.41*	*1.07*	*0.91*	*1.57*
EBITDA/EV	20.4%	4.0%	1.04%	-0.60	11.53	1.17	1.11	1.77
	17.3%	*4.5%*	*0.96%*	*0.07*	*5.80*	*1.04*	*0.89*	*1.54*
OPE/EV	20.2%	3.7%	1.00%	-0.83	9.03	1.19	1.11	1.81
	17.5%	*4.7%*	*0.93%*	*-0.40*	*4.57*	*1.09*	*0.91*	*1.61*
EBITDA/P	19.8%	3.4%	1.01%	-0.55	9.74	1.15	1.09	1.73
	16.9%	*4.1%*	*0.96%*	*0.09*	*5.14*	*1.01*	*0.88*	*1.49*
OPE/P	19.0%	2.7%	0.99%	-0.84	9.36	1.13	1.05	1.71
	16.7%	*4.0%*	*0.93%*	*-0.28*	*4.88*	*1.04*	*0.88*	*1.53*
E(Adj.)/P	19.8%	3.5%	1.04%	-0.66	7.52	1.12	1.04	1.68
	17.6%	*4.9%*	*1.00%*	*-0.21*	*4.50*	*1.03*	*0.89*	*1.52*
EBIT/EV	18.6%	2.4%	1.00%	-0.78	11.91	1.09	1.03	1.67
	16.0%	*3.3%*	*0.93%*	*-0.09*	*5.38*	*0.99*	*0.83*	*1.47*
E/P	18.5%	2.3%	1.02%	-0.63	8.65	1.07	1.00	1.61
	16.3%	*3.7%*	*0.97%*	*-0.10*	*4.54*	*0.97*	*0.83*	*1.42*
S/EV	18.2%	2.1%	1.09%	-0.66	11.05	0.98	0.95	1.45
	14.2%	*1.8%*	*1.01%*	*-0.07*	*4.00*	*0.80*	*0.70*	*1.13*
EBIT/P	16.6%	0.6%	0.97%	-0.84	11.95	1.00	0.93	1.51
	14.4%	*1.9%*	*0.91%*	*-0.10*	*5.50*	*0.90*	*0.76*	*1.32*
D/P	15.9%	-0.1%	0.99%	-0.80	8.03	0.93	0.90	1.44
	13.5%	*1.1%*	*0.96%*	*-0.33*	*4.10*	*0.80*	*0.72*	*1.22*
B/EV	16.5%	0.7%	1.16%	-0.26	6.78	0.83	0.84	1.18
	12.4%	*0.3%*	*1.08%*	*0.04*	*2.55*	*0.65*	*0.59*	*0.88*
B/P	15.8%	0.1%	1.16%	-0.28	7.45	0.80	0.80	1.13
	10.8%	*-1.2%*	*1.09%*	*0.11*	*3.23*	*0.55*	*0.50*	*0.75*
S/P	15.0%	-0.8%	1.07%	-0.72	11.17	0.81	0.78	1.18
	11.5%	*-0.7%*	*0.99%*	*-0.09*	*4.02*	*0.64*	*0.56*	*0.90*

	Top20							
	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F
Market	15.5%	0.0%	0.92%	-1.42	14.30	0.98	0.86	1.49
	11.9%	*0.0%*	*0.85%*	*-0.70*	*6.40*	*0.78*	*0.62*	*1.16*
OPE+D&A/EV	27.3%	9.9%	1.17%	0.16	11.99	1.40	1.41	2.21
	22.7%	*9.3%*	*1.04%*	*0.22*	*5.02*	*1.29*	*1.11*	*1.93*
CF/EV	23.9%	7.0%	1.21%	0.23	13.42	1.19	1.18	1.85
	20.1%	*7.1%*	*1.05%*	*-0.20*	*4.04*	*1.13*	*0.93*	*1.65*
CF/P	23.3%	6.5%	1.14%	-0.52	8.82	1.22	1.18	1.88
	20.5%	*7.4%*	*1.04%*	*-0.02*	*4.45*	*1.15*	*0.98*	*1.71*
OPE+D&A/P	22.4%	5.7%	1.10%	-0.44	10.03	1.21	1.20	1.82
	19.0%	*6.1%*	*1.02%*	*0.21*	*5.14*	*1.10*	*0.97*	*1.61*
E(Adj)/EV	23.3%	6.6%	1.19%	0.09	10.23	1.16	1.16	1.78
	19.5%	*6.6%*	*1.07%*	*-0.10*	*4.08*	*1.07*	*0.92*	*1.56*
EBITDA/EV	21.4%	4.8%	1.17%	0.35	13.17	1.09	1.11	1.67
	17.3%	*4.5%*	*1.04%*	*0.35*	*6.03*	*0.97*	*0.85*	*1.41*
OPE/EV	21.1%	4.5%	1.12%	0.02	14.10	1.11	1.10	1.73
	17.7%	*4.8%*	*0.97%*	*-0.21*	*4.11*	*1.06*	*0.87*	*1.54*
EBITDA/P	20.8%	4.3%	1.09%	-0.53	11.32	1.13	1.11	1.71
	17.7%	*4.9%*	*1.01%*	*0.22*	*5.30*	*1.02*	*0.89*	*1.49*
OPE/P	20.3%	3.9%	1.06%	-0.78	9.66	1.13	1.07	1.70
	17.1%	*4.3%*	*0.97%*	*-0.11*	*4.20*	*1.03*	*0.85*	*1.49*
E(Adj.)/P	20.3%	4.0%	1.11%	-0.55	6.91	1.09	1.05	1.62
	17.5%	*4.8%*	*1.04%*	*-0.12*	*3.96*	*0.98*	*0.86*	*1.42*
EBIT/EV	18.5%	2.3%	1.13%	0.21	15.67	0.96	0.97	1.49
	15.3%	*2.7%*	*0.98%*	*0.16*	*5.87*	*0.89*	*0.75*	*1.30*
E/P	18.7%	2.5%	1.08%	-0.43	8.93	1.02	0.99	1.52
	16.0%	*3.4%*	*1.01%*	*0.10*	*5.13*	*0.91*	*0.80*	*1.33*
S/EV	17.2%	1.2%	1.15%	-0.14	12.32	0.88	0.87	1.31
	12.1%	*-0.2%*	*1.03%*	*0.07*	*4.05*	*0.66*	*0.57*	*0.92*
EBIT/P	18.2%	2.0%	1.05%	-0.58	12.95	1.02	0.99	1.54
	15.7%	*3.0%*	*0.96%*	*0.30*	*6.58*	*0.94*	*0.80*	*1.37*
D/P	15.7%	-0.3%	1.06%	-0.70	7.53	0.86	0.85	1.35
	13.2%	*0.9%*	*1.02%*	*-0.23*	*4.02*	*0.73*	*0.67*	*1.13*
B/EV	16.9%	1.1%	1.37%	0.22	10.46	0.72	0.76	1.05
	11.4%	*-0.6%*	*1.22%*	*0.33*	*3.49*	*0.52*	*0.47*	*0.71*
B/P	12.5%	-2.8%	1.26%	-0.22	8.95	0.57	0.57	0.79
	8.9%	*-2.9%*	*1.15%*	*0.08*	*2.66*	*0.41*	*0.37*	*0.55*
S/P	14.1%	-1.5%	1.18%	0.28	14.96	0.69	0.69	1.01
	9.7%	*-2.3%*	*1.04%*	*0.14*	*5.05*	*0.51*	*0.44*	*0.70*

Appendix 2. Returns for the momentum sample

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current sample market. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the momentum sample overall technology sector. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios.

Top30%

	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F
Market_Mome	14.7%	0.0%	0.93%	-1.37	14.05	0.91	0.82	1.39
	11.0%	0.0%	0.86%	-0.66	6.22	0.70	0.57	1.03
Mome_6-1m	19.1%	3.8%	1.06%	-0.86	9.82	1.06	0.99	1.59
	15.6%	4.1%	1.00%	-0.42	6.72	0.90	0.76	1.31
OPE+D&A/EV	20.4%	4.6%	0.95%	-0.97	10.61	1.27	1.15	1.97
	17.6%	5.7%	0.88%	-0.43	5.39	1.16	0.94	1.74
CF/EV	22.2%	6.2%	0.97%	-0.99	10.44	1.36	1.23	2.10
	19.3%	7.3%	0.90%	-0.44	4.70	1.25	1.02	1.88
CF/P	21.0%	5.2%	0.97%	-1.07	11.05	1.29	1.16	2.01
	18.4%	6.5%	0.90%	-0.45	5.36	1.19	0.97	1.80
E(Adj.)/EV	18.3%	2.9%	0.97%	-0.86	8.39	1.11	1.01	1.68
	15.4%	3.8%	0.91%	-0.49	5.04	0.97	0.80	1.43
E(Adj.)/P	18.3%	2.9%	0.98%	-0.78	7.33	1.10	1.00	1.65
	15.8%	4.2%	0.93%	-0.42	4.68	0.97	0.82	1.44
S/EV	17.4%	2.1%	1.00%	-0.86	12.39	1.02	0.97	1.52
	13.1%	1.7%	0.93%	-0.18	4.41	0.80	0.68	1.14
OPE+D&A/EV + M	20.7%	4.9%	0.97%	-0.91	10.87	1.27	1.16	1.97
	17.6%	5.7%	0.90%	-0.39	6.57	1.13	0.94	1.71
CF/EV + M	19.6%	3.9%	0.95%	-1.20	12.16	1.22	1.09	1.89
	16.3%	4.5%	0.87%	-0.62	5.89	1.08	0.86	1.61
CF/P + M	18.9%	3.4%	0.96%	-1.16	11.29	1.16	1.03	1.79
	15.7%	4.0%	0.89%	-0.64	5.98	1.01	0.81	1.51
E(Adj.)/EV + M	19.2%	3.6%	0.97%	-1.09	9.80	1.17	1.04	1.78
	16.6%	4.9%	0.91%	-0.69	6.37	1.06	0.85	1.57
E(Adj.)/P + M	19.6%	4.0%	0.96%	-1.02	9.76	1.20	1.07	1.84
	17.0%	5.2%	0.90%	-0.60	6.13	1.09	0.89	1.63
S/EV + M	17.7%	2.3%	0.96%	-1.01	12.30	1.09	1.00	1.66
	15.2%	3.6%	0.90%	-0.32	5.36	0.98	0.82	1.44
50/50 Mo_OPE+D&A/EV	19.9%	4.4%	0.95%	-1.18	11.99	1.25	1.12	1.93
	16.8%	5.1%	0.88%	-0.62	6.58	1.10	0.90	1.66
50/50 Mo_CF/EV	20.8%	5.2%	0.95%	-1.26	11.95	1.30	1.16	2.01
	17.6%	5.9%	0.88%	-0.68	6.07	1.16	0.94	1.74
50/50 Mo_CF/P	20.3%	4.7%	0.95%	-1.27	12.17	1.26	1.13	1.95
	17.2%	5.5%	0.88%	-0.68	6.33	1.13	0.91	1.69
50/50 Mo_E(Adj.)/EV	18.9%	3.5%	0.96%	-1.14	10.84	1.17	1.05	1.78
	15.7%	4.1%	0.89%	-0.67	6.49	1.01	0.82	1.49
50/50 Mo_E(Adj.)/P	19.0%	3.5%	0.96%	-1.08	10.18	1.16	1.05	1.77
	15.9%	4.3%	0.90%	-0.63	6.31	1.02	0.83	1.50
50/50 Mo_S/EV	18.4%	3.1%	0.96%	-1.19	13.44	1.13	1.04	1.72
	14.4%	3.0%	0.89%	-0.54	6.13	0.93	0.77	1.36

Top20%

	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F
Market_Mome	14.7%	0.0%	0.93%	-1.37	14.05	0.91	0.82	1.39
	11.0%	0.0%	0.86%	-0.66	6.22	0.70	0.57	1.03
Mome_6-1m	22.1%	6.6%	1.20%	-0.62	8.75	1.10	1.05	1.63
	18.1%	6.6%	1.14%	-0.18	6.00	0.93	0.82	1.35
OPE+D&A/EV	25.3%	8.8%	1.03%	-0.65	9.63	1.47	1.39	2.27
	22.1%	9.7%	0.95%	-0.11	4.62	1.37	1.16	2.06
CF/EV	22.7%	6.7%	1.04%	-0.68	8.82	1.30	1.22	1.99
	19.4%	7.3%	0.97%	-0.30	4.99	1.17	0.99	1.74
CF/P	20.6%	4.8%	1.03%	-0.83	9.46	1.18	1.09	1.80
	18.1%	6.2%	0.97%	-0.27	4.95	1.09	0.91	1.61
E(Adj.)/EV	21.1%	5.4%	1.07%	-0.59	7.46	1.17	1.11	1.78
	18.2%	6.4%	1.01%	-0.29	4.79	1.06	0.91	1.56
E(Adj.)/P	19.4%	3.9%	1.07%	-0.62	7.29	1.07	1.01	1.61
	17.3%	5.6%	1.02%	-0.20	4.57	0.98	0.86	1.45
S/EV	17.4%	2.1%	1.09%	-0.65	11.35	0.94	0.91	1.38
	13.3%	1.9%	1.01%	-0.09	4.33	0.75	0.65	1.05
OPE+D&A/EV + M	19.7%	4.1%	1.03%	-0.90	11.09	1.13	1.05	1.73
	17.3%	5.4%	0.96%	-0.34	5.81	1.05	0.88	1.56
CF/EV + M	18.4%	2.9%	1.02%	-1.05	10.30	1.06	0.97	1.61
	15.2%	3.6%	0.95%	-0.57	6.07	0.92	0.76	1.35
CF/P + M	19.4%	3.8%	1.01%	-1.03	9.93	1.13	1.03	1.71
	16.2%	4.5%	0.94%	-0.54	5.43	1.00	0.82	1.46
E(Adj.)/EV + M	19.7%	4.0%	1.02%	-0.98	10.18	1.15	1.05	1.73
	16.8%	5.0%	0.94%	-0.52	5.51	1.04	0.86	1.51
E(Adj.)/P + M	19.3%	3.6%	1.00%	-0.95	9.41	1.14	1.05	1.71
	16.7%	4.8%	0.93%	-0.51	5.25	1.04	0.86	1.52
S/EV + M	15.6%	0.5%	1.04%	-0.77	12.48	0.87	0.82	1.30
	13.2%	1.8%	0.98%	-0.11	6.35	0.76	0.65	1.11
50/50 Mo_OPE+D&A/EV	24.0%	8.0%	1.02%	-1.01	11.47	1.41	1.30	2.17
	20.4%	8.4%	0.95%	-0.40	5.85	1.27	1.06	1.90
50/50 Mo_CF/EV	22.8%	7.0%	1.02%	-1.09	10.72	1.33	1.22	2.04
	19.1%	7.3%	0.95%	-0.54	5.47	1.18	0.98	1.75
50/50 Mo_CF/P	21.8%	6.1%	1.02%	-1.15	11.04	1.27	1.16	1.93
	18.5%	6.8%	0.95%	-0.55	5.33	1.14	0.94	1.68
50/50 Mo_E(Adj.)/EV	22.0%	6.3%	1.04%	-1.04	10.05	1.26	1.16	1.92
	18.6%	6.8%	0.97%	-0.57	5.72	1.12	0.93	1.65
50/50 Mo_E(Adj.)/P	21.2%	5.6%	1.04%	-1.00	9.95	1.21	1.11	1.82
	18.1%	6.4%	0.98%	-0.50	5.55	1.08	0.91	1.59
50/50 Mo_S/EV	20.0%	4.6%	1.03%	-0.97	12.69	1.15	1.08	1.74
	15.9%	4.4%	0.96%	-0.32	5.69	0.96	0.81	1.40

Top20

	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F
Market_Mome	14.7%	0.0%	0.93%	-1.37	14.05	0.91	0.82	1.39
	11.0%	0.0%	0.86%	-0.66	6.22	0.70	0.57	1.03
Mome_6-1m	21.1%	5.6%	1.26%	-0.41	8.01	1.00	0.98	1.46
	16.6%	5.1%	1.16%	-0.05	5.87	0.83	0.72	1.18
OPE+D&A/EV	28.3%	11.5%	1.16%	0.10	12.37	1.47	1.47	2.34
	23.7%	11.1%	1.02%	0.12	4.99	1.38	1.17	2.07
CF/EV	23.7%	7.6%	1.20%	0.33	13.64	1.18	1.18	1.85
	19.5%	7.5%	1.04%	-0.17	4.50	1.10	0.92	1.62
CF/P	21.5%	5.7%	1.13%	-0.54	8.90	1.13	1.07	1.73
	18.5%	6.6%	1.04%	-0.05	4.49	1.04	0.88	1.54
E(Adj.)/EV	23.4%	7.4%	1.19%	0.08	11.13	1.17	1.17	1.82
	19.6%	7.6%	1.06%	-0.15	4.45	1.08	0.93	1.60
E(Adj.)/P	20.5%	4.8%	1.10%	-0.56	6.87	1.10	1.05	1.64
	17.7%	5.9%	1.04%	-0.15	4.33	0.99	0.86	1.45
S/EV	16.9%	1.6%	1.18%	-0.02	12.27	0.84	0.83	1.26
	11.7%	0.3%	1.05%	0.12	4.56	0.62	0.53	0.87
OPE+D&A/EV + M	20.4%	4.7%	1.08%	-0.77	10.59	1.11	1.05	1.70
	18.5%	6.5%	1.00%	-0.24	5.62	1.08	0.91	1.60
CF/EV + M	17.4%	2.0%	1.03%	-0.82	8.19	1.00	0.93	1.49
	15.3%	3.7%	0.96%	-0.51	5.51	0.92	0.77	1.35
CF/P + M	18.0%	2.5%	1.03%	-0.87	8.25	1.02	0.95	1.51
	16.3%	4.5%	0.96%	-0.47	4.76	0.98	0.82	1.42
E(Adj.)/EV + M	18.3%	2.9%	1.05%	-0.81	8.44	1.03	0.96	1.53
	16.3%	4.5%	0.97%	-0.43	4.60	0.97	0.81	1.39
E(Adj.)/P + M	18.1%	2.7%	1.04%	-0.79	8.26	1.02	0.96	1.52
	15.9%	4.1%	0.96%	-0.46	4.82	0.95	0.80	1.37
S/EV + M	17.9%	2.5%	1.08%	-0.74	13.10	0.97	0.92	1.45
	15.0%	3.4%	0.99%	-0.09	6.28	0.87	0.74	1.26
50/50 Mo_OPE+D&A/EV	25.1%	8.9%	1.07%	-0.69	11.18	1.41	1.34	2.16
	20.6%	8.5%	0.97%	-0.24	6.09	1.25	1.04	1.85
50/50 Mo_CF/EV	22.8%	7.0%	1.07%	-0.80	10.29	1.27	1.19	1.93
	18.5%	6.7%	0.97%	-0.49	5.07	1.12	0.92	1.62
50/50 Mo_CF/P	21.8%	6.1%	1.06%	-1.04	10.59	1.22	1.14	1.85
	18.0%	6.3%	0.97%	-0.48	4.83	1.09	0.89	1.58
50/50 Mo_E(Adj.)/EV	22.7%	6.9%	1.09%	-0.79	9.59	1.25	1.17	1.88
	18.6%	6.8%	0.99%	-0.49	5.16	1.10	0.91	1.60
50/50 Mo_E(Adj.)/P	21.2%	5.6%	1.07%	-0.91	9.31	1.18	1.11	1.76
	17.5%	5.9%	0.98%	-0.46	5.34	1.04	0.87	1.50
50/50 Mo_S/EV	19.6%	4.2%	1.07%	-0.72	11.83	1.08	1.03	1.63
	14.5%	3.0%	0.96%	-0.31	4.69	0.86	0.72	1.23

Appendix 3. Returns for the forward-looking samples

This table reports the compound annual growth rate and market-adjusted compound annual growth rate from 31.3.2006 until 4.1.2021. Market-adjusted returns are computed using the current technology sector market portfolio. Standard deviation, skewness and kurtosis are reported for the raw returns. Risk-adjusted measures Sharpe ratio, Sortino ratio and Sortino_F ratio are also reported for all multiples. Market stands here for the forward-looking samples overall technology sector. The value below with the grey background and formatted in italic stands for the value before Covid-19 crisis (31.3.2006-31.1.2020). Top 30% corresponds to the top 30% portfolios with the multiple in question, Top 20% to the top 20% portfolios and Top 20 to the top 20 portfolios.

	Top30%								Top20%								Top20							
	CAGR	M-Ad. CAGR	Std. dev.	Skewness	Kurtosis	Sharpe	Sortino	Sortino_F	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F	CAGR	M-Ad.	Std. dev.	Skew.	Kurt.	Sharpe	Sort.	Sort_F
Market (EBITDA)	13.1%	0.0%	0.94%	-1.15	11.47	0.80	0.72	1.20	13.1%	0.0%	0.94%	-1.15	11.47	0.80	0.72	1.20	13.1%	0.0%	0.94%	-1.15	11.47	0.80	0.72	1.20
	9.5%	*0.0%*	*0.87%*	*-0.63*	*6.35*	*0.59*	*0.48*	*0.85*	*9.5%*	*0.0%*	*0.87%*	*-0.63*	*6.35*	*0.59*	*0.48*	*0.85*	*9.5%*	*0.0%*	*0.87%*	*-0.63*	*6.35*	*0.59*	*0.48*	*0.85*
LTM_EBITDA/EV	16.8%	3.1%	0.99%	-0.83	9.57	0.99	0.92	1.48	16.8%	3.0%	1.01%	-0.76	9.81	0.97	0.92	1.44	17.1%	3.3%	1.02%	-0.66	9.00	0.98	0.94	1.45
	13.9%	*3.8%*	*0.94%*	*-0.33*	*5.11*	*0.84*	*0.72*	*1.23*	*13.8%*	*3.8%*	*0.94%*	*-0.27*	*5.12*	*0.83*	*0.71*	*1.20*	*13.5%*	*3.5%*	*0.95%*	*-0.26*	*4.97*	*0.81*	*0.70*	*1.16*
LTM OPE+D&A/EV	15.1%	1.6%	0.99%	-0.77	9.06	0.88	0.83	1.31	15.9%	2.3%	1.02%	-0.68	9.10	0.90	0.86	1.33	16.8%	3.1%	1.04%	-0.65	8.95	0.95	0.91	1.40
	12.0%	*2.1%*	*0.94%*	*-0.35*	*5.40*	*0.72*	*0.61*	*1.03*	*12.5%*	*2.6%*	*0.96%*	*-0.27*	*5.01*	*0.73*	*0.63*	*1.05*	*12.6%*	*2.7%*	*0.96%*	*-0.27*	*4.89*	*0.74*	*0.63*	*1.05*
12F_EBITDA/EV	15.5%	1.9%	1.01%	-0.76	9.77	0.89	0.84	1.31	17.0%	3.3%	1.07%	-0.59	9.41	0.93	0.90	1.37	17.0%	3.4%	1.09%	-0.51	9.80	0.91	0.90	1.35
	11.5%	*1.7%*	*0.96%*	*-0.27*	*5.20*	*0.67*	*0.58*	*0.96*	*13.0%*	*3.1%*	*1.01%*	*-0.11*	*4.91*	*0.73*	*0.64*	*1.05*	*12.7%*	*2.8%*	*1.02%*	*-0.02*	*5.23*	*0.70*	*0.62*	*1.01*
Market (EBIT)	12.5%	0.0%	0.94%	-1.17	11.47	0.76	0.68	1.14	12.5%	0.0%	0.94%	-1.17	11.47	0.76	0.68	1.14	12.5%	0.0%	0.94%	-1.17	11.47	0.76	0.68	1.14
	8.9%	*0.0%*	*0.87%*	*-0.65*	*6.29*	*0.55*	*0.44*	*0.80*	*8.9%*	*0.0%*	*0.87%*	*-0.65*	*6.29*	*0.55*	*0.44*	*0.80*	*8.9%*	*0.0%*	*0.87%*	*-0.65*	*6.29*	*0.55*	*0.44*	*0.80*
LTM_EBIT/EV	13.3%	0.7%	1.01%	-0.78	7.76	0.76	0.70	1.11	12.8%	0.2%	1.03%	-0.77	8.29	0.71	0.66	1.03	13.2%	0.5%	1.04%	-0.70	7.95	0.73	0.68	1.05
	10.5%	*1.3%*	*0.96%*	*-0.44*	*4.66*	*0.60*	*0.51*	*0.85*	*10.3%*	*1.2%*	*0.99%*	*-0.39*	*4.63*	*0.57*	*0.49*	*0.81*	*10.4%*	*1.3%*	*0.99%*	*-0.38*	*4.48*	*0.57*	*0.50*	*0.81*
LTM_OPE/EV	13.7%	1.0%	1.00%	-0.72	7.15	0.79	0.73	1.15	13.1%	0.5%	1.05%	-0.77	8.79	0.71	0.66	1.04	12.4%	-0.1%	1.05%	-0.67	7.41	0.67	0.63	0.97
	10.6%	*1.4%*	*0.95%*	*-0.43*	*4.76*	*0.61*	*0.52*	*0.88*	*10.6%*	*1.5%*	*1.00%*	*-0.38*	*4.95*	*0.59*	*0.50*	*0.84*	*9.6%*	*0.6%*	*1.01%*	*-0.37*	*4.84*	*0.52*	*0.45*	*0.74*
12F_EBIT/EV	16.2%	3.2%	1.01%	-0.73	7.64	0.93	0.87	1.39	17.1%	4.0%	1.05%	-0.63	7.62	0.95	0.90	1.41	17.6%	4.5%	1.07%	-0.56	7.33	0.97	0.92	1.43
	13.0%	*3.7%*	*0.97%*	*-0.42*	*5.40*	*0.76*	*0.66*	*1.11*	*13.9%*	*4.5%*	*1.00%*	*-0.30*	*5.24*	*0.78*	*0.69*	*1.14*	*14.5%*	*5.1%*	*1.01%*	*-0.27*	*5.16*	*0.82*	*0.72*	*1.19*
Market (E)	13.2%	0.0%	0.93%	-1.30	12.72	0.81	0.72	1.23	13.2%	0.0%	0.93%	-1.30	12.72	0.81	0.72	1.23	13.2%	0.0%	0.93%	-1.30	12.72	0.81	0.72	1.23
	9.6%	*0.0%*	*0.86%*	*-0.70*	*6.55*	*0.61*	*0.48*	*0.88*	*9.6%*	*0.0%*	*0.86%*	*-0.70*	*6.55*	*0.61*	*0.48*	*0.88*	*9.6%*	*0.0%*	*0.86%*	*-0.70*	*6.55*	*0.61*	*0.48*	*0.88*
LTM_E/EV	15.4%	1.9%	1.01%	-0.77	7.17	0.89	0.82	1.32	15.4%	1.8%	1.06%	-0.70	7.36	0.84	0.78	1.24	15.0%	1.5%	1.08%	-0.58	6.96	0.80	0.76	1.17
	12.2%	*2.3%*	*0.96%*	*-0.48*	*4.98*	*0.71*	*0.60*	*1.03*	*11.7%*	*1.9%*	*1.01%*	*-0.37*	*4.89*	*0.65*	*0.56*	*0.94*	*11.6%*	*1.8%*	*1.02%*	*-0.36*	*4.69*	*0.64*	*0.55*	*0.92*
LTM_E/P	13.0%	-0.3%	1.00%	-0.71	7.33	0.74	0.68	1.09	14.1%	0.7%	1.07%	-0.60	7.19	0.76	0.72	1.12	14.1%	0.8%	1.09%	-0.65	7.77	0.75	0.71	1.09
	10.1%	*0.4%*	*0.96%*	*-0.41*	*5.50*	*0.58*	*0.49*	*0.84*	*11.0%*	*1.3%*	*1.02%*	*-0.28*	*4.97*	*0.60*	*0.52*	*0.87*	*10.5%*	*0.9%*	*1.03%*	*-0.26*	*4.73*	*0.56*	*0.49*	*0.81*
12F_E/EV	17.5%	3.7%	1.02%	-0.90	8.79	1.01	0.94	1.52	19.4%	5.4%	1.09%	-0.64	7.26	1.05	0.99	1.56	18.4%	4.5%	1.12%	-0.60	7.39	0.97	0.93	1.44
	15.2%	*5.0%*	*0.96%*	*-0.45*	*4.87*	*0.91*	*0.77*	*1.33*	*16.8%*	*6.5%*	*1.04%*	*-0.29*	*4.64*	*0.93*	*0.82*	*1.37*	*16.1%*	*5.9%*	*1.06%*	*-0.27*	*4.33*	*0.88*	*0.77*	*1.28*
12F_E/P	16.0%	2.3%	1.01%	-0.79	8.19	0.92	0.85	1.37	16.2%	2.5%	1.07%	-0.67	8.01	0.89	0.84	1.31	16.1%	2.4%	1.09%	-0.57	7.12	0.86	0.83	1.27
	13.6%	*3.6%*	*0.97%*	*-0.41*	*5.27*	*0.80*	*0.68*	*1.17*	*13.7%*	*3.7%*	*1.02%*	*-0.23*	*4.35*	*0.77*	*0.67*	*1.10*	*13.3%*	*3.3%*	*1.03%*	*-0.21*	*4.15*	*0.73*	*0.64*	*1.05*
Market (S)	13.3%	0.0%	0.93%	-1.33	13.13	0.82	0.73	1.25	13.3%	0.0%	0.93%	-1.33	13.13	0.82	0.73	1.25	13.3%	0.0%	0.93%	-1.33	13.13	0.82	0.73	1.25
	9.8%	*0.0%*	*0.86%*	*-0.71*	*6.48*	*0.62*	*0.49*	*0.91*	*9.8%*	*0.0%*	*0.86%*	*-0.71*	*6.48*	*0.62*	*0.49*	*0.91*	*9.8%*	*0.0%*	*0.86%*	*-0.71*	*6.48*	*0.62*	*0.49*	*0.91*
LTM_S/EV	14.6%	1.0%	1.01%	-0.93	10.18	0.83	0.78	1.21	11.1%	-2.1%	1.08%	-0.87	9.75	0.58	0.55	0.81	11.2%	-2.0%	1.10%	-0.84	10.20	0.57	0.55	0.81
	10.8%	*0.8%*	*0.96%*	*-0.34*	*4.44*	*0.62*	*0.53*	*0.87*	*7.9%*	*-1.8%*	*1.03%*	*-0.30*	*3.85*	*0.40*	*0.36*	*0.55*	*8.1%*	*-1.7%*	*1.03%*	*-0.26*	*3.92*	*0.42*	*0.36*	*0.57*
12F_S/EV	13.3%	-0.2%	1.02%	-0.99	10.30	0.74	0.70	1.07	13.3%	-0.2%	1.09%	-0.81	9.03	0.70	0.66	0.99	11.5%	-1.8%	1.13%	-0.59	10.38	0.57	0.56	0.82
	9.9%	*0.0%*	*0.96%*	*-0.42*	*4.33*	*0.56*	*0.48*	*0.78*	*9.5%*	*-0.4%*	*1.03%*	*-0.33*	*3.67*	*0.50*	*0.44*	*0.68*	*8.3%*	*-1.5%*	*1.05%*	*-0.18*	*4.33*	*0.42*	*0.36*	*0.57*