SIZE, ENHANCED VALUE, MOMENTUM, AND COMBINATION STRATEGIES: THE DENMARK EVIDENCE

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Examiner: University Lecturer Henri Huovinen

ABSTRACT

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Size, enhanced value, momentum, and combination strategies: The Denmark evidence

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Keywords: anomalies, size anomaly, value anomaly, value investing, valuation multiples, momentum, value and momentum, composite value, combination ratio, combination strategies, value enhancements, factors, portfolio performance, Denmark

This paper considers the performance of several popular portfolio strategies related to size, value, momentum anomalies, and their combinations in the Denmark stock market during the 2002-2022 period. The collected stocks are evaluated based on their market capitalization, the performance of composite value and past 6-month price and dividend momentum, skipping the most recent month. In addition, the combination strategies of separate pure-play portfolios are examined. Moreover, the performance of size factor (SMB), value factor (HML) and momentum factor (WML) was additionally analyzed.

Partly in line with the results of many popular studies, our results indicate that small firms offer higher returns and, with some metrics, higher risk-adjusted returns than large firms. Furthermore, based on the received results, combining value and momentum offers some enhancements to composite value. Value enhancement especially applies to momentum long-only strategy as it can increase raw and risk-adjusted returns while decreasing the volatility of a pure value strategy. Of the pure-play portfolios, Winner's portfolio offered the highest raw returns, while high value mainly had the best risk-adjusted returns. Overall, the high value outperformed the low value in every category, which aligns with similar studies' results. In turn, the results of factors were also aligned with other studies, where the WML performed the best, and SMB was weakest in returns.

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Tämä tutkielma huomioi useiden suosittujen sijoitusstrategioiden suoriutumista, jotka liittyvät koko, arvo ja momentum anomalioihin, sekä niiden yhdistelmiin Tanskan osakemarkkinoilla ajanjaksolla 2002–2022. Kerätyt osakkeet arvioidaan perustuen niiden markkina-arvoon, yhdistetyn arvostuskertoimen suoriutumiseen ja kuuden edellisen kuukauden hinta ja osinko momentumin perusteella, ohittaen viimeisin kuukausi. Näiden lisäksi yhdistelmästrategioita tutkitaan yhdistelemällä muodostettuja yhden strategian osakesalkkuja. Tutkielmassa tarkastellaan myös koko faktorin (SMB), arvofaktorin (HML) ja momentum faktorin (WML) suoriutumista.

Tutkimuksen tulokset olivat osittain linjassa useiden tunnettujen tutkimusten kanssa ja osoittavat pienyhtiöiden tarjoavan suuremmat tuotot ja joillain riskikorjatuilla menetelmillä korkeampaa riskikorjattua tuottoa verrattuna suuriin yrityksiin. Lisäksi saatujen tulosten perusteella arvostrategian yhdistäminen momentum vaikutuksen kanssa tarjoaa joitain parannuksia yhdistettyyn arvoon. Arvostrategiaa voidaan erityisesti parantaa momentum long-only strategialla, koska se samanaikaisesti lisää arvostrategian raakatuottoja ja riskikorjattuja tuottoja, sekä vähentää volatiliteettia. Kaikista yhden strategian salkuista, voittajat suoriutuivat parhaiten raakatuotoissa ja korkean arvon strategia pääosin riskikorjatuissa tuotoissa. Kaiken kaikkiaan, korkea arvo suoriutui kaikilla menetelmillä paremmin kuin matalan arvon salkku, joka on linjassa samankaltaisten tutkimusten tuloksien kanssa. Puolestaan faktorien tulokset olivat myös linjassa muiden tutkimusten kanssa, joissa WML suoriutui parhaiten ja SMB heikoiten tuotoissa.

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1 Introduction

It is generally accepted that, in some form, market efficiency exists; hence studies have shifted to observing inefficiencies through market anomalies. Market anomalies are crucial to investors seeking to gain an edge against their peers and outperform them, while to academics, they are essential critical components in explaining inefficiency and its causes. Market anomalies are deviations from the norm, i.e., the academic framework called "Efficient Market Hypothesis" (see: Fama, 1970). These deviations of EMH mean that, in practice, investors could earn statistically and reliably higher returns than the market on average by systematically utilizing these deviations in their investment strategy (Zacks, 2011, 5). Additionally, market anomalies can indicate inconsistencies in academic asset pricing models with empirical evidence (Schwert, 2003, 3). Meanwhile, investors have seen an opportunity to exert academic research on anomalies in their investment strategies. These strategies are most commonly related to value anomaly (Basu, 1977; Basu, 1983), small firm anomaly (Banz, 1981) and momentum anomaly (JEGADEESH and TITMAN, 1993).

Often it is argued whether value strategy is relevant as an investment strategy considering the diminishing value premium and the higher returns of growth stocks after the financial crisis (Blitz and Hanauer, 2020, 64). However, contrary to popular belief, increasing intangibles do not cause value's death (Israel, Laursen and Richardson, 2020, 51). At the same time, value's poor performance for decades could be explained by the weak performance of a typical academic measure for value (HML) (Blitz and Hanauer, 2020, 77). In turn, the performance of value strategy has been enhanced by combining firm size on numerous studies from the early days. Small firm studies' first "wave" found empirical evidence for higher returns in small-cap stocks (Banz, 1981; Reinganum, 1981; ROLL, 1981). The enhancement has gone further in recent years with the addition of the momentum factor to value (Asness, Clifford S., 1997; ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013; Cakici, Fabozzi and Tan, 2013; Fama and French, 2012; Fisher, Shah and Titman, 2015; Foye, 2016; Grobys and Huhta-Halkola, 2019; Hanauer, Matthias X. and Linhart, 2015b; Leivo, Timo H. and Pätäri, 2011; Leivo, Timo H., 2012). The momentum factor could improve the lagging returns of value due to its much stronger performance recently (i.e., 2010 – 2019) (Blitz, 2020, 61). The combination of value and momentum has received plenty of attention from academics; however, the research on Nordic equity markets is very thin. While Denmark has been included in some international value and momentum studies, it is generally under Europe or Nordic-wide samples (Fama and French, 2012; Grobys and Huhta-Halkola, 2019). Foye (2016) suggested that having such wide samples could cause the weakening of the size effect (Foye, 2016, 249). Furthermore, the author of this thesis has not found any studies implementing more "sophisticated" value metrics introduced by Blitz and Haneuer (2020) combined with momentum, especially in the Denmark stock market.

1.1 Study purpose

This study aims to fill the research gap in the Nordic equity market, especially in Denmark, while observing the performance of size, value, and momentum effects. Furthermore, the study aims to provide information on these effects on the country-specific level, as Europe-wide or Nordic-wide samples may subdue the actual performance (see: Chui, Titman and Wei, 2010; Foye, 2016). The primary focus of this thesis will be NASDAQ Copenhagen from 2002 to 2022. The period was chosen to have similar market conditions at the start and end year. Instead of using generic book-to-market (B/M) solely to measure value, this study will use an "enhanced" metric. The primary motivator for the valuation metrics used was Blitz and Haneuer (2020). While their study did not include momentum, it offered immense insight into different value strategies and performance metrics. The secondary aim of this thesis is to find whether momentum complements with value, increasing its performance. Studies have indicated that momentum would increase returns of value portfolio in bull markets while decreasing returns in bear markets (see: Leivo, Timo H., 2012). However, some studies have indicated that momentum does not offer significant benefits (see: Brown, S., Du, Rhee and Zhang, 2008). Portfolios are formed for firm size, composite value, and momentum separately, and lastly, combining value with firm size and value with momentum. In order to find whether anomalies offer any reasonable excess returns, their performance is compared to the performance of the market portfolio. The chosen market portfolio is OMX Copenhagen Benchmark GI.

The main research question is:

- Are there significant size, value, and momentum effects in NASDAQ Copenhagen from 2002 to 2022?

Four supporting questions were established to support the main research question:

- Does enhanced value outperform OMX Copenhagen Benchmark GI?
- Does the addition of small firms to enhanced value increase its performance?
- Does the addition momentum factor increase enhanced value portfolio performance?
- Does enhanced value and momentum long-only perform better than enhanced value and momentum long-short strategy?

1.2 Limitations and structure

This study examines the performance of pure size, value and momentum portfolios and their combinations. Combined portfolios are constructed by combining pure-play portfolios. Data consists of individual stocks from NASDAQ Copenhagen. Constructed portfolios are equally weighted, and market-cap weighted portfolios are not included. The portfolio consists of 10 stocks due to the small population of firms at the start year. However, according to the study of Alexeev and Dungey (2015), the firm-specific is lowered sufficiently (90%) for an equally weighted portfolio of 10 stocks. Furthermore, this study does not consider the variability effect between the stocks (covariance) in constructed portfolios. Book values and other financial statement information are lagged for 6 months. An enhanced value portfolio is created using the average ranking method on CF/P, EBITDA/EV, B/M and NPY performance. For the measurement of momentum, a total return for the past 6-month price and dividend is used, skipping the most recent month. All formed portfolios are rebalanced each year in June. Noteworthy is that since the examined data consists of the largest and smallest firms, which are picked without any percentile market cap, the long-short strategy may not be practical as small-cap firms are not commonly short-sellable. Taxes, transaction costs and short-selling costs have been excluded from this study. The performance of constructed portfolios is compared to the index and their peers in respective categories. Finally, combination portfolios are compared to pure-play portfolios to determine whether the combination improves portfolio performance. The chosen index is OMX Copenhagen Benchmark GI, as it considers both the price increase and reinvested dividends, forming a better market performance measurement (Nasdaq, 2023). Noteworthy is that the Benchmark GI was chosen as other indices do not exist throughout the whole sample period from 2002 to 2022.

Additionally, individual factors are examined utilizing three-factor and four-factor models; however, the models are not used for computing portfolio returns. Firms that do not have adequate financial information (i.e., missing financial statements from a year) are eliminated from this study and firms in the financial industry, correspondingly to Fama and French (1992). According to them, financial firms utilize high leverage, generally viewed as a risk factor or abnormal for non-financial firms (FAMA and FRENCH, 1992, 429).

The structure of the study consists of five main chapters, which are the following: the introduction, literature review, data and methods, results, and discussion. The first chapter introduces the background and research while explaining this study's purpose and motivation. The second chapter focuses on the research of central concepts, contradictions and research methods. The third chapter introduces the data utilized and methods for portfolio formation and performance analysis. The fourth chapter presents study results and a summary of pure-play and combination portfolios. The final chapter discusses the study results, conclusions, and the study validity and reliability review.

2 Review of literature

This section reviews the literature on market efficiency, size effect, value premium, performance on enhanced value ratios, momentum, and the combination of value and momentum. Moreover, criticism towards the main concepts is presented.

2.1 Market efficiency

Generally, it is suggested that markets are efficient if the publicly available information is reflected in the prices of the stocks rapidly (Zacks, 2011, 2). The academic foundation of the Efficient Market Hypothesis (EMH) is often attributed to Fama (1965, 98; 1970, 416), who concluded that evidence supports the random-walk theory and that the efficient markets model is comprehensive. Random walk is a theory in which the changes in stock prices should be unpredictable and random (Bodie, Kane and Marcus, 2021, 332). Comparable conclusions to market rapidly adapting new information to security prices were researched by Fama, Fisher, Jensen, and Roll (1969) and Ball and Brown (1968). It was found that 85 to 90 % of new annual income information was reflected in the security prices during the same month (Ball and Brown, 1968, 176). In a more recent study, evidence suggested that after the announcement of earnings, mispricing is less than five per cent in highly competitive markets (Bernard and Thomas, 1990, 339). However, Grossman and Stiglitz (1980, 405) suggested that markets cannot be entirely efficient, considering market transactions for different information remains. De Bondt and Thaler's (1987, 579) evidence indicates that investors, in the short term, overreact to changes in firm earnings, supporting the claim that markets are not entirely efficient. Meanwhile, Battalio and Mendenhall (2005, 317) found that particularly small investors cause seasonal random walks, trading in the opposite direction than the general signals suggest, during the post-earnings announcements.

It was commonly thought that the prices of securities would swiftly adjust to any new information instantly and make any acts of achieving greater returns futile, whether it is technical or fundamental analysis. The "random walk" concept is closely related to the efficient market hypothesis. In short, the consequent price of the security behaves in a random pattern compared to initial prices. (Malkiel, 2003, 59) Mandelbrot (1966) argued that even if a non-random walk model is constructed, it could not be used to increase profits. Mandelbrot's framework is called a "fair game model" because it assumes that market equilibrium states expected returns and the prices of securities consist of all information (Fama, 1970, 385). Kendall (1953) studied 22 industrial stock weekly prices and stated: "In series of prices which are observed at fairly close intervals, the random changes from one term to the next are so large as to swamp any systematic effect which may be present. The data behave almost like wandering series" (Kendall and Hill, 1953, 11).

The examination of market efficiency is divided into three tests based on the framework of Fama (1970): weak form, semi-strong form, and strong form. In weak-form tests, historical prices of the securities are inspected to determine whether they affect current prices. Semi-strong form tests examine whether publicly available information, such as stock splits and earnings, are rapidly reflected in the price. Lastly, in strong form tests, it is tested if any individual investor or a coalition has access to meaningful information that the generality of common investors does not have. (Fama, 1970, 383)

Studies of weak form tests are comprehensive and support the efficient market model, although there is evidence of dependency on daily price changes and returns, according to Fama (1970). He argues that the studies of Kendall (1953) and Cootner (1962) are in line with the "fair game" model and that there is scarce evidence against the random walk model. Fama also adds that this dependency can be used to profit marginally, though transaction costs will absorb most of the returns. Therefore, Fama claims that the evidence of positive dependency is not adequate to contradict the efficient markets model, and even evidence of longer dependences on day-to-day price changes is hard to find against the "fair game" model. (Fama, 1970, 414)

While both Kendall (1953) and Cootner (1962) reported a small serial correlation for the prices of individual companies, Kendall (1953, 11) argues that if the individual stock does not behave differently from the similar average stock, it is not possible to predict their movements week ahead without specific relevant information. In contrast, Cootner (1962, 39) demonstrated that investors could achieve superior results when comparing the current price to the average price of the last 200 days and buying the stock if it is higher than the moving average and selling short if it less than the moving average; however, he continued that this is not a viable option after considering the transaction costs. According to Cootner (1962), these findings do not imply non-randomness (i.e., do not contradict random-walk theory) because the net returns are not rewarding. Other common examples of weak-form tests are the studies on the momentum effect found by Jegadeesh and Titman (1993).

The earliest studies of semi-strong form tests are from Fama, Fisher, Jensen and Roll (1969) and Ball and Brown (1968). Fama, Fisher, Jensen and Roll's (1969) evidence suggests that the market realizes stock splits as an indication of dividend increases, thus adjusting "fully" the stock price by the end of the split month. They conclude that the stock market is "efficient" and the only possible way to use splits to increase returns is to utilize some form of inside information (Fama, Fisher, Jensen and Roll, 1969, 20). Ball and Brown (1968, 176) found that only 10 to 15 % of report income has been anticipated by the end of the month and 20 % at the time of the release. Furthermore, accounting income numbers explain about half of the net effect of all information available in the 12 months prior to their release, though the net effect is only 20% of the value of all information in the released month (Ball and Brown, 1968, 176). Most anomalies fall into semi-strong tests because they test how companies' fundamentals affect the stock price (Bodie, Kane and Marcus, 2021, 349). Fama (1970, 415) suggests that strong-form tests should be viewed as benchmarks for market efficiency and studies that contradict the strong form are related to corporate insider and monopolistic information.

Consequently, it remains a question why academics retain the EMH despite many studies (Banz, 1981; Basu, 1977; Bondt and Thaler, 1987; De Bondt and Thaler, 1985; Grossman and Stiglitz, 1980; JEGADEESH and TITMAN, 1993; Rouwenhorst, K. Geert, 1998) indicating flaws on it? According to Kuhn, anomalies can only emerge when theoretical frameworks and concepts have developed to a point where deviations are recognizable

(Kuhn, 1962, 763). EMH is a valid framework for examining inefficiencies because, without any widely accepted framework, various anomalies could not have been researched at the profound level as previous studies have.

2.2 Size effect

Size anomaly is an effect where small-cap stocks perform better returns than large-cap stocks (Ciliberti et al., 2019, 58). The earliest observations of the size effect were documented by Banz (1981, 17), who suggested that higher returns may form due to less popular securities lacking information and limiting diversification. Roll (1981, 887) proposed that small firms generate excessive returns due to incorrectly estimated risk resulting from less frequent trading. However, Cristopher and Edminister (1983) did not find evidence of liquidity premium, though they aligned with the conclusions of previous studies (i.e., Banz, 1981; Reinganum, 1981) confirming the size premium. Reinganum (1982, 35) argued that size could be, with certainty, seen as an empirically prominent effect. The combination of the size effect and the January effect was first studied by Keim (1983), who concluded that approximately 50% of the size effect was caused by the January effect, though evidence from Ronald C. (1988) indicates that size effect and earnings-to-price effect exist even after removing January effect. Daniel and Titman (1997, 6) suggest that high book-to-market (B/M) and small firm premium in returns is not formed through their co-movement and that size anomaly is an effect solely occurring in January. Patel (2016) concluded that the January effect does not exist anymore, neither in the bull market nor bear market, when he studied US and international markets from 1997 to 2014. Similar evidence was provided by Marquering, Nisser and Valla (2006), which included the disappearances of the turn-of-the-year, weekend, and holiday effects. Nonetheless, even some of the most recent studies argue that the size effect is seasonal, forming strong positive effects in January and adverse effects in the last quarter (Fays, Hübner and Lambert, 2022).

Reinganum (1992, 6) revealed that from 1926 to 1989, nearly any small-cap portfolio outperformed a large-cap portfolio on average. However, the disappearance of the size effect has been empirically proven in multiple studies, which reveal that the size effect may have been a specifically strong phenomenon in 1980 – 1989 (Amihud, 2002; Dichev, 1998; Isberg and Thies, 1992; Louis, Karceski and Lakonishok, 2000). According to Schwert (2003, 47-48), publications of academic papers on the size effect have weakened it because some investors have taken advantage of the findings, causing its disappearance. Horowitz, Loughran and Savin (2000) suggest that size premium is diminishing as investors become more aware of its existence or as the rising popularity of index funds that weigh more often large firms. According to Hou and van Dijk (2010), the size effect disappeared as the cause of the negative cash flow shocks in small firms, which consequently caused lower returns than expected, while large firms experienced positive cash flow shocks and higher returns than expected (Hou and Van Dijk, 2010, 2).

Nonetheless, there have been several attempts to resurrect size premium despite previous studies indicating its disappearance (Alquist, Israel and Moskowitz, 2018; Asness, Clifford, Frazzini, Israel, Moskowitz and Pedersen, 2018; Cheema, Chiah and Zhong, 2021; Hou and van Dijk, 2019). While evidence from Alquist et al. (2018) did not establish any compelling empirical evidence to support standalone size premium, both Cheema, Chiah and Zhong (2021) and Hou and van Dijk (2019) found a prominent size premium after adjusting profitability shocks for the returns of small and large firms. Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018, 507) documented a steadier and higher size effect when controlling for quality (e.g., profitability), as the mixed results of previous studies were affected by the erratic performance of small "junk" firms.

Internationally size effect has been extensively studied by various researchers (Brown, P., Keim, Kleidon and Marsh, 1983; Elfakhani, Lockwood and Zaher, 1998; Fama and French, 2017; Kato and Schallheim, 1985; Lischewski and Voronkova, 2012; Rouwenhorst, K. G., 1999). Keim, Kleidon and Marsh (1983) found in the Australian market that for the smallest firms, the average size premium was at least 4 % per month. Elfakhani, Lockwood and Zaher (1998) found evidence supporting the relationship between returns and size in the Canadian market. Blitz and Vidojevic (2019) suggest that small caps with higher B/M and higher past returns deliver higher returns than their rivals. Fama and French (2017, 457) found that average returns increase for small firms in North America, Europe, and Asia Pacific with a book-to-market (B/M) ratio. Size effect has also received considerable research in Europe (Amel-Zadeh, 2011; Foye, 2016; Heston, Rouwenhorst and Wessels, 1999b; Karathanasis, Kassimatis and Spyrou, 2010; Pandey, Mittal and Mittal, 2021). Amel-Zadeh (2011) confirmed the size effect in the German stock market and found that small firms underperform against large firms in bear markets, while in the bull markets, the relationship is reversed (Amel-Zadeh, 2011, 34 - 35). Karathanasis, Kassimatis and Spyrou (2010) and Foye (2016) found a statistically significant size premium in Denmark. Results from Karathanasis et al. present that both small and large firms have significantly lower returns from February to December when compared to January (Karathanasis, Kassimatis and Spyrou, 2010, 156). Based on these results, it could be argued that both small-cap and large-cap portfolios suffer in Denmark from the "January effect". Foye (2016, 248 - 249) explains that Fama and French (2012) did not find a size premium in Europe but found value and momentum premium because they studied Europe as a whole. Furthermore, Foye (2016, 249) suggests that size premium can only be observed at the country level, while value and momentum are Europe-wide. Foye's reasoning might also explain why Grobys and Huhta-Halkola (2019) did not find a size premium in the Nordic stock market.

Size effect has presumably faced more controversy than any other investment strategy after its discovery. Some studies have suggested that size premium is mainly driven by the earnings-to-price ratio (E/P) (Basu, 1983; Kross, 1985). In contrast, others do not consider it an anomaly (Berk, Jonathan, 2000). Results from Kross (1985) indicate that E/P is a more powerful explanatory variable when both the market value and earnings yield has been decomposed as separate measurements. Likewise, Basu (1983) concluded that size is an indirect effect of higher returns and dominated by the E/P ratio, while Reinganum (1981) claimed that E/P was dominated by size. Nonetheless, some researchers consider both size and E/P equally significant (Jaffe, Keim and Westerfield, 1989). Arnott (2005) concluded that the market capitalization effect is much weaker when the value-versus-growth effect is separated from the size effect, and the value effect is much stronger than commonly assumed. Lambert, Fays, and Hubner (2016, 50) documented the size effect forming at the turn of the year, while the value effect was strong throughout the year. Zivney and Thompson (1987) provided contradictory evidence compared to past studies as they managed to eliminate most of the size effect with a one-year buy-and-hold strategy and using relative price ratio as a predictor. Fama, French, Booth, and Sinquefield's (1993) results revealed that the difference between returns of similar-sized stocks disappeared after the risk premium was adjusted with B/M.

Reasons for the appearance of size premium have been comprehensively proposed. Often small firms are in the stages of early business cycles and experience higher growth when the production and sales are scaled up. However, it is commonly seen that larger firms are financially more stable and at a more mature stage, explaining why growth is not as steep. Evans (1987, 568) studied 100 manufacturing industries from 1976 to 1980 and found that firm growth decreases when the firm size and age increase. Carlson, Fisher and Giammarino (2004, 2600) displayed a linear relationship between beta and growth opportunities. In other words, with higher growth opportunities, there lies greater risk and vice-versa, which indicates that the premium from small firms is influenced by more significant risk within the Capital Asset Pricing Model (CAPM). Kim and Burnie (2002) state that small firms have higher financial leverage and lower productivity, so they are sensitive to market conditions. Moreover, their results suggest that the small firm effect emerges in the "expansion phase" of its economic cycle (Kim and Burnie, 2002, 123 - 124).

The liquidity of small firms has often been offered as an explanation for abnormal excess return, while evidence for this is contradictory. Stoll and Whaley (1983) argue that small firm premium is affected by higher transaction costs due to their risk and illiquidity. Furthermore, they suggest monitoring costs are higher for small firms, though infrequent trading does not explain size anomalies using monthly data (Stoll and Whaley, 1983, 58). Amihud and Mendelson (1986, 44) note that investors should consider both liquidity and risk in investment decisions because there is little to be done to avoid illiquidity costs. Pastor and Stambaugh (2003) find that stocks more sensitive to aggregate liquidity have abnormal returns, even if market returns, size, value and momentum are considered. Their results reveal that, due to the smallest stocks being less liquid, they have the highest aggregate sensitivity (Pástor and Stambaugh, 2003, 21- 22). Novy-Marx (2004) concludes that premium does not emerge from holding illiquid assets as they do not offer momentous returns compared to liquid assets. Illiquidity could indicate other underlying risk factors, which are therefore compensated with higher returns (Novy-Marx, 2004, 17).

Dimson and Marsh (1999) documented reversals of size premium due to changes in fundamentals and sentiment in the UK from 1955 to 1997. While according to Al-Rjoub (2005), after the results of Banz (1981), partial reversals were higher for larger firms, generating a higher excess return for large-cap portfolios than small-cap portfolios (i.e., "large-firm effect"). Patel (2012) argues that neither size premium nor size reversal exists in developed or emerging markets when he studied them from 1996 to 2010. Additionally, Patel suggests that market conditions do not matter for the emergence of size premium, and while size premium was higher in January, it is not significant compared to other months (Patel, 2012, 659).

The relationship between beta and risk has also been offered to explain the size premium. Bhardwaj and Brooks's (1993) results of bull and bear scenarios for small and large firms in NYSE and AMEX from 1926 to 1988 reveal that small firms entail higher systematic risk in a bull market than in a bear market, whereas for large firms, this systematic risk is more negligible. Furthermore, large firms outperform small firms in other months besides January, while the "January effect" is smaller for small firms if risks can vary in bull and bear months (Bhardwaj and Brooks, 1993, 282). Heston, Rouwenhorst and Wessels (1999a) found in 12 European markets that stock returns and firm size have a negative relationship, whilst, for beta, this relationship is positive.

Furthermore, different biases could distort the results of the studies, such as survivor bias and restatement bias. In survivor bias, firms no longer listed are exempted from data; in restatement bias, only restated figures, such as revenue, are used instead of initial figures (Zacks, 2011, 304). Survivorship bias can be corrected by considering it through data collection and handpicking the dataset (Lischewski and Voronkova, 2012, 23).

In conclusion, there is no clear consensus or empirical evidence to this perpetual question of whether the size effect exists permanently. However, based on previous studies, it can be stated that the size effect is time, market, and research model dependent. Therefore, even though contradicting evidence of the size effect is vast, the author of this study will include the size factor as a suggestion from Esakia, Goltz, Luyten and Sibbe (2019, 44), as the exclusion of the size factor raises unexplained returns from 64% to 86%.

2.3 Value premium

Value anomaly, also known as value premium, is an effect where stocks with high earnings-to-price (E/P), book-to-market (B/M) and dividends-to-price (D/P) ratios earn excessive returns compared to Capital Asset Pricing Model (CAPM) (Schwert, 2003, 11). The empirical discovery of value anomaly is often credited to Basu (1977), who documented that high earnings-to-price (E/P) portfolios notably outperformed low E/P portfolios in 1957-1971. Similar findings for high E/P significantly affecting returns were confirmed in numerous studies (BANZ and BREEN, 1986; Basu, 1983; Chan, Hamao and Lakonishok, 1991; FAMA and FRENCH, 1992; Jaffe, Keim and Westerfield, 1989; Lakonishok, Shleifer and Vishny, 1994). Nevertheless, it has been much discussed whether value stocks mainly achieve their better returns either by the irrational behaviour of the investors, causing mispricing or being a compensation for the perhaps higher risk (Zacks, 2011, 267).

Effects of B/M have likewise been researched extensively, and the evidence supports high B/M stocks performing better than low B/M stocks (Chan, Hamao and Lakonishok, 1991; Chen, Petkova and Zhang, 2008; Daniel, Titman and Wei, 2001; Davis, Fama and French, 2000; Fama and French, 2006; FAMA and FRENCH, 1992; Fama and French, 1993). Results from Chan, Hamao and Lakonishok (1991) present that B/M and cash-flow-to-price (CF/P) influenced the most expected returns instead of size by market capitalization and E/P. Findings from Chan and Lakonishok (2004, 84) reveal that value stocks have higher returns and are not riskier than growth stocks, and the manifestation of the value premium is more evident for small-cap stocks. Loughran (1997, 267) suggests that B/M does not have credible predicting power for returns, and it has become statistically insignificant since 1963 due to fund managers investing in large-cap stocks with high B/M and thus diminishing the effect. Hou, Karolyi and Kho (2011) studied the performance of valuation ratios in 49 countries from 1981 to 2003 and found that CF/P outperformed both E/P and D/P immensely in developed countries. Furthermore, in Denmark highest monthly returns were achieved with momentum (4.43%), B/M (1.02%) and CF/P (0.17%) (Hou, Karolyi and Kho, 2011, 2535). Pätäri, Leivo, Hulkkonen and Honkapuro (2018, 838) propose, based on their results from the German stock market from 2000 to 2015, that combination ratios may be the best method for investors to profit from anomalies and that a combination of CF/P and S/P produces best raw returns and second-best risk-adjusted returns (Sharpe).

Presumably, the first study to investigate the performance of combined value metrics was from Dhatt, Kim and Mukherji (1999). Their results suggest that combined value metrics increase monthly average returns and retain standard deviation (i.e., volatility) or even lower it (Dhatt, Kim and Mukherji, 1999, 64 - 65). Dhatt, Kim and Mukherji (2004) concluded that out of any single valuation ratio, high CF/P has the lowest risk and best risk-adjusted returns (Dhatt, Kim and Mukherji, 2004, 45). Meanwhile, Leivo and Pätäri (2009) suggest that the highest returns are achieved with either D/P or combination portfolios, based on the results from the Finnish stock market (Leivo, T. H. and Pätäri, 2009, 84). According to Novy-Marx (2013), value can be enhanced with profitability without an increase in risk. In conclusion, empirical evidence from previous studies proves that investors can remarkably benefit from combination ratios in both raw and adjusted returns.

The value premium is generally accepted as a prominent effect among researchers; however, the reasons behind its performance are challenged. The criticism can be divided into two different views, which are risk and behavioural views. According to the risk view, value can be seen as a proxy for risk (FAMA and FRENCH, 1992, 452). Additionally, it is suggested by certain studies that the risk is due to firms" relative financial distress (Fama and French, 1996). Zhang (2005, 96) explains that credit crunches are commonly associated with value stocks distress and raising the risk level; however, he concludes that the results of the distress hypothesis are highly varied. Some academics propose that the B/M ratio positively affects returns because high B/M firms are riskier due to their higher operating leverage (Carlson, Fisher and Giammarino, 2004, 2600). According to the operating leverage hypothesis, B/M and expected returns are strong within and weak across industries (Novy-Marx, 2011, 104). Vassalou and Xing (2004) argue that the size effect and B/M effect are both related to default risk. Moreover, they suggest that value stocks, high BM stocks and small firms achieve greater returns only because their default risk is higher than growth stocks and large firms (Vassalou and Xing, 2004, 866). Cooper (2006) suggests that B/M encompasses a firm's excess capital and, as a result, affects risk and returns. According to Cooper, book value is relatively constant when the market value falls as a reaction to negative profitability shocks, thus causing a high B/M for the firm, whilst, in positive profitability shocks, such a firm can expand its production with its excess capital capacity, without need to invest considerably (Cooper, 2006, 139). According to Penman, Reggiani, Richardson and Tuna (2018, 32), B/P is characteristic of risk because it contains earnings growth expectations and the risk of failing expectations.

The behavioural view is often associated with De Bondt and Thaler (1985), who found that market overreaction is more considerable to firms experiencing extreme losses than capital gains, explaining the 25% higher returns for "losers". In other words, overreaction could cause a value premium since the "undervalued" price is corrected later. Lakonishok, Shleifer, and Vishny (1994) found that investors extrapolate past earnings growth rates of "glamour" (i.e., popular stocks) stocks and assume that the same level of growth is continued. This extrapolation of earnings might be one of the reasons explaining why the value strategy performs better. Moreover, they suggest that value stocks have better returns than "glamour" stocks due to lower value relative to price and lower fundamental risk (Lakonishok, Shleifer and Vishny, 1994, 27). Shleifer and Vishny (1997) suggest that arbitrageurs avoid value stocks because of their unpredictability. Moreover, according to them, in extreme situations, arbitrageurs have the urge to liquidate their positions, which does not lessen a stock's mispricing (Shleifer and Vishny, 1997, 22).

This study is motivated to use more "sophisticated" methods for measuring value by the results of Blitz and Hanauer (2020). According to Asness, Frazzini, Israel, and Moskowitz

(2015), the best method to measure value is a composite variable, even though a composite portfolio of B/M, E/P, CF/P and D/P performs worse than single ratios (excl. D/P), and out of the single ratios, E/P and CF/P performed the best average returns in 1951 to 2014. However, noteworthy is that the composite portfolio performs better risk-adjusted returns due to 20% lower volatility (Asness, Clifford, Frazzini, Israel and Moskowitz, 2015, 43). Furthermore, they compared the Sharpe ratio by decades and found that CF/P had been the strongest from 2001 to 2014, while from 1991 to 2000, it had suffered from tremendously poor performance (Asness, Clifford, Frazzini, Israel and Moskowitz, 2015, 44). Moreover, this study uses a composite ratio together with momentum due to the composite ratio's robust link to higher performance (Asness, Clifford, Frazzini, Israel and Moskowitz, 2015, 43).

Chan, Hamao and Lakonishok (1991) studied size, cash flow yield, book-to-market and earnings yield on the Japanese stock market between 1971 to 1988. They found a positive impact between book-to-market and cash-to-flow on expected returns (Chan, Hamao and Lakonishok, 1991, 3). Furthermore, they suggest that CF/P could be a stronger predictor of returns than E/P (Chan, Hamao and Lakonishok, 1991, 13). Meanwhile, Kessler, Scherer and Harries (2019) studied US large-cap equities from 1988 to 2017. They found that CF/P had median average annualized returns close to P/E (Kessler, Scherer and Harries, 2019, 32). Based on the results reviewed in this chapter, it could be stated that CF/P is at least as powerful as P/E.

Loughran and Wellman (2011) studied the relationship between returns EV/EBITDA in NYSE, AMEX, and NASDAQ from 1963 to 2009. The lowest decile equal-weighted portfolio for EV/EBITDA achieved monthly returns of 1.73%, and the highest decile equal-weighted EV/EBITDA portfolio had monthly returns of 0.91%. In other words, value firms had higher returns than growth stock returns as low EV/EBITDA depicts value stocks and high EV/EBITDA growth stocks. In value-weight comparison, the lowest decile (1.23%) and the highest decile (0.59%) suffered in returns against equally weighted portfolios. (Loughran and Wellman, 2011, 1636)

Supporting evidence for the performance of EBITDA/EV was found by Gray and Vogel (2012) from 1971 to 2010 in NYSE, AMEX, and NASDAQ. Their results indicated that EBITDA/EV outperformed other value metrics as equally weighted high EBITDA/EV portfolio had annual returns of 17.66, whereas the high E/M portfolio and the high B/M portfolio generated returns of 15.25% and 15.03%, respectively (Gray and Vogel, 2012, 114 - 116). Extensive international evidence of EV/EBITDA was presented by Walkshäusl and Lobe (2015, 783) when they studied 40 different countries outside of the US individually from 1981 to 2010. The results of Denmark present that the low EV/EBITDA (high EBITDA/EV) portfolio generates monthly returns of 0.72%, whereas the high EV/EBITDA (low EBITDA/EV) returns are 0.33% (Walkshäusl and Lobe, 2015, 790). In this study, inversed EV/EBITDA is utilized; therefore, high EBITDA/EV depicts value stocks and low EBITDA/EV growth stocks. Based on the results reviewed before, high EBITDA/EV should increase returns significantly, and it could be a stronger predictor of returns than E/P.

Fama and French (1992) studied NYSE, AMEX, and NASDAQ from 1962 to 1989 while excluding financial firms due to their high leverage. They argue that to ensure the availability of accounting data, a 6-month gap between fiscal yearend and returns is needed (FAMA and FRENCH, 1992, 446). Their results demonstrate that the highest returns in B/M portfolios were primarily achieved in small market equity firms, as for the three smallest market equity firms (ME) with the highest B/M, the monthly average returns were 1.60% - 1.92%, while for the three largest market equity firms with the highest B/M monthly average returns were 1.18% - 1.55% (FAMA and FRENCH, 1992, 446). In conclusion, it can be stated, based on the results of Fama and French, that returns grow with higher B/M metrics and smaller firm sizes.

Boudoukh, Michaely, Richardson and Roberts (2007) found that payout yields are more substantially correlated with returns than dividend yields in the cross-section. Monthly returns for NPY portfolios were 1.24% (low), 1.36% (medium), and 1.57% (high), whilst returns for dividend yields portfolios were in respective order 1.15%, 1.28% and 1.33% (Boudoukh, Michaely, Richardson and Roberts, 2007, 6). They argue that dividend yields have lost their attraction and that total payout yield is a more suitable metric because, according to their findings, after the 1982 SEC rule 10b-18, repurchase activity was potent as it became a means for firms to distribute earnings to shareholders (Boudoukh, Michaely, Richardson and Roberts, 2007, 37). Walkshäusl (2016) provided international evidence of NPY by studying 20 equity markets from 1994 to 2014. According to his results, firms with high net payout yield generated average raw monthly returns of 1.33% and firms with low net payout yield of 0.59% (Walkshausl, 2016, 61). Based on the reviewed studies, NPY premium is extensive, prominent in both US and international markets and possibly a stronger predictor for returns than dividend yield.

2.4 Momentum

Momentum is an empirically proven effect where securities that have performed better (winners) than rival securities (losers) are also likely to continue their outperformance further (Asness, Clifford, Frazzini, Israel and Moskowitz, 2014, 76). The roots of momentum were established by De Bondt and Thaler (1987; 1985), who studied the performance of stocks with intense capital gains ("winners") and stocks with intense capital losses ("losers"). Their results were that loser portfolios generated 25% of excess returns compared to winner portfolios after 36 months of portfolio formation (De Bondt and Thaler, 1985, 804). Furthermore, they argue that the winner-loser effect is unrelated to firm size, even though small firms are part of the "loser-firm effect" (Bondt and Thaler, 1987, 579). Research by Jegadeesh and Titman (1993) is commonly viewed as the first implementation of a long-short momentum strategy. Their results suggest that buying winners and selling past losers based on their 6-month past returns and holding them for 6 months accomplishes a compounded excess return of approximately 12% per year from 1965 to 1989 (JEGADEESH and TITMAN, 1993, 89). Moreover, they confirmed that their results for abnormal profits of momentum strategy were not due to data snooping by extending the data sample to 1997 on NYSE and AMEX (Jegadeesh and Titman, 2001, 5, 20). Rouwenhorst (1998, 282) provided similar results on an international scale when he studied momentum in 12 European countries, finding that the portfolio of winners outperformed the portfolio of losers by 1% per month. Carhart (1997, 58) studied momentum in mutual funds, concluding that transaction costs absorb abnormal returns from momentum strategy in funds.

A combination of value and momentum was studied by Asness (1997, 34), who discovered a negative correlation between them, which statistical results could explain as the value was momentous with losers, while momentum was more prominent for expensive firms. Grundy and Martin (2001, 29) confirmed a significant momentum effect on NYSE and AMEX from 1926 to 1995, where risk-adjusted monthly returns of 1.3% were stable across sample data and poor performance in January is explained by the size factor. Griffin, Ji, and Martin (2005, 38) found that momentum generates more profits on long-positions rather than short-positions, price and earnings momentum is best used together, and momentum is volatile because it may cause negative returns for 3-5 years in the US and 39 non-US countries from 1975 to 1995. Moreover, they find that Denmark has a negative correlation between earnings momentum and price, while generally, for the majority, it was a positive correlation of under 0.40 (Griffin, Ji and Martin, 2005, 8). Asness, Frazzini and Israel (2014) suggest that returns from long-position and short-position are evenly balanced and that momentum can also be captured with long-only positions (Asness, Clifford, Frazzini, Israel and Moskowitz, 2014, 79). Fisher, Shah and Titman (2015, 38 - 39) presented that a 50/50 value momentum portfolio underperformed against pure value-weighted portfolios (B/M) in small-cap and large-cap stocks because of low momentum premium. Moreover, they suggest that a long-only portfolio may have an advantage in small-cap stocks due to lower transaction costs from lower turnover relevant to small-cap stocks, while benefits are only moderate in large-cap stocks (Fisher, Shah and Titman, 2015, 47).

Grobys and Huhta-Halkola (2019, 2881) concluded that momentum, together with value, increases risk-adjusted returns (Sharpe) and lowers risk (standard deviation) in Nordic equity markets from 1993 to 2017. Leivo and Pätäri (2011) found that the 130/30 long-short value momentum strategy substantially outperforms the long-only value momentum strategy in the Finnish stock market from 1993 to 2008. Moreover, they documented that composite portfolio can significantly benefit from a long-short strategy as B/P, D/P and EV/EBITDA portfolio achieved 5.5% higher annual returns and only a 1% increase in volatility, compared to the long-only value portfolio (Leivo, Timo H. and Pätäri, 2011, 413). Brown, Du, Rhee, and Zhang (2008) puzzlingly found that a combined portfolio of value and momentum did not provide substantial enhancements in performance for a single strategy value portfolio in

Asian markets from 1995 to 2005. Furthermore, they suggest that pure momentum portfolios are sensitive to the holding period and weighting (Brown, S., Du, Rhee and Zhang, 2008, 87). According to Chui, Titman and Wei (2010, 375 - 376), momentum is more robust in individualistic countries (US) due to underreaction, while in less individualistic countries (Japan) B/M effect is more prevalent (Chui, Titman and Wei, 2010, 375 - 376). Momentum has also been broadly studied in emerging markets (Cakici, Fabozzi and Tan, 2013; Hanauer, Matthias X. and Linhart, 2015a; Hanauer, Matthias X. and Linhart, 2015b; Rouwenhorst, K. G., 1999), Asia (Brown, S., Du, Rhee and Zhang, 2008; Chui, Wei and Titman, 2000), and separately in Japan (Asness, Clifford, 2011; Hanauer, Matthias, 2014).

Moskowitz and Grinblatt (1999) show that momentum strategies are not diversified because of the tendency of winner and loser firms in the same industry. Furthermore, industry-based momentum generates higher profits, either evenly balanced or lean to the buy side, while most stock momentum strategies generate profits mainly from the sell side (Moskowitz and Grinblatt, 1999, 1286). Chordia and Shivakumar's (2002, 986) results suggest that momentum profits are driven by macroeconomic variables related to the business cycle as momentum returns disappear when stock prices are adjusted to macroeconomic variables, and momentum returns are negative in recessions, though statistically insignificant. Griffin, Ji and Martin (2003, 2539) studied whether momentum is driven by macroeconomic risk, not finding any evidence that aggregate stock market movements or movements of GDP are related to the profitability of momentum. According to Berk, Green and Naik (1999, 1586), change in expected returns and risk over time is affected by individual firm's projects, and momentum strategy is profitable only in the short-term as information on the firm's assets is essential and firms with low-risk projects have experienced the most significant price increases; therefore long-term effects of these projects diminish over time and lower expected returns on momentum strategies. Sadka (2003) finds that liquidity risk explains a part of momentum returns, and momentum strategies that generate high risk-adjusted returns are related to low levels of liquidity. However, a recent study from Li, Novy-Marx and Velikov (2019, 225, 248) suggests no significant evidence supporting Pastor and Stambaugh's (2003) claim that liquidity risk is half the momentum effect. According to Daniel and Moskowitz (2016, 242), although momentum has been acknowledged as a statistically robust phenomenon worldwide, it experiences prolonged crashes in states of extreme turmoil in equity markets since losers are commonly shorted in momentum strategies as they usually experience future capital losses; however, this effect is inversed in the rebound from bear markets, meaning that losers generate higher returns than winners.

2.5 Size, value, and momentum

This thesis conforms to the framework of Assness, Moskowitz and Pedersen (2013) with adjustments while expanding the research to the Denmark stock market. Adjustments for this study regard value metrics and the addition of size factor. The data and methods section views the portfolio construction in more detail. This section reviews common frameworks for value and momentum studies and their results. Asness, Moskowitz and Pedersen (2013) studied value and momentum in four equity markets: the United States, Continental Europe, the United Kingdom, and Japan. They found extensive evidence of value and momentum premiums across all asset classes and discovered the negative correlation between value and momentum, corresponding to the results of Asness (1997).

Asness et al. (2013) did find only moderate evidence for the value and momentum link between the business cycle, default risk and consumption. Nonetheless, they found significant evidence for the positive relationship between momentum and liquidity risk and a negative relationship between value and liquidity risk in all inspected asset classes. They suggest that the reversal movements relating to liquidity risk could partly explain why value and momentum are negatively correlated, even if the liquidity risk is only a small portion of the co-movement. Furthermore, they argue that an equal-weighted portfolio of value and momentum will eliminate the liquidity risk and generate considerably higher returns. (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 931)

For the measurement of value, they used a book-to-market ratio (B/M), and their values lagged for 6 months for the availability of the data for investors, while the most recent market values were used. Momentum (MOM) was measured with the past 12-month cumulative raw returns. The most recent month's return was skipped to avoid 1-month reversal returns, which could be explained by liquidity or, as Grinblatt and Moskowitz (2004) suggested, to avoid microstructure bias. (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 936)

Concluding results of the pure portfolios of Asness et al. (2013), the high-value portfolio was better than the low-value portfolio in every category, including returns, Sharpe, Alpha, and volatility. In momentum portfolios, high momentum portfolio performed better almost in every other category than low momentum portfolio, besides volatility (standard deviation). (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 940)

Concluding the results of the combination portfolios of Asness et al. (2013), the 50/50 combination of value and momentum complemented each other, as returns and Sharpe increased, and volatility significantly decreased, while Alpha did also decrease, it was only by 0.1% (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 940). In Europe, they received similar results as in the US, where combination portfolios greatly enhanced the performance of value strategy in every category (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 941).

James Foye (2016) studied size, value, and momentum effects on Europe on a country-specific with three-factor and four-factor models extending the research of Fama and French (2012), as Europe was studied as a singular unit. The sample period was from 1998 to 2013, and stocks were categorized by size (market equity), momentum and B/P for specific countries and aggregate Europe. Portfolios were constructed for size, momentum, and B/P (Foye, 2016, 225).

The size was measured with SMB (small minus big), value with HML (high minus low) and momentum with WML (winners versus losers). In comparison, the market risk premium is the performance of the market portfolio minus the one-month German bond rate. The results in Europe the monthly returns were for mean market risk premium (0.1981), for SMB

(0.0119), for HML (0.0299) and WML (0.2394). In Denmark, monthly returns for factors were 2.9110, 0.0811, 0.2534 and -1.3477. (Foye, 2016, 227 - 228)

In Denmark, monthly returns were from 4.35% - 5.59% for the two smallest in size portfolios, while for the two largest in size, 1.21% - 2.10% (Foye, 2016, 229). When including WML (four-factor model), the highest monthly returns were in the two smallest portfolios with the highest B/P (Foye, 2016, 241). Based on the results from Foye (2016), it can be generally viewed that the combination of firm size and value can achieve higher excess returns, particularly in small-cap space, while the results for the performance of momentum in Denmark deviated from the rest of Europe.

3 Data and Methods

This section will introduce the data utilized and methods for portfolio formulation. Moreover, computing methods for returns, volatility, and risk-adjusted returns are reviewed.

The performance of portfolios is evaluated on the 20-year sample from 2002 June to 2022 June. The sample data consists of financial statement information of listed firms on NASDAQ Copenhagen. The financial data, excluding stock prices, are extracted from Refinitiv Eikon as it does not provide adjusted monthly prices; therefore, Yahoo Finance was used. Yahoo Finance adjusted monthly price notices, dividends paid to shareholders, and stock splits. As the risk-free rate, a periodical monthly average of Denmark's 3-month T-bill rate is extracted from Eikon. Following this logic, when utilizing a risk-free rate for calculations of a portfolio from 2002 to 2003, an average monthly risk-free rate of Denmark's 3-month T-bill rate from 2002 to 2003 is used.

For illustration, the performance of 3-month bond yields is presented during December in Appendix 1. Noteworthy is that the German Bubill does not have data before 2005 in Eikon. Meanwhile, the pure data of Copenhagen Benchmark GI from Refinitiv Eikon is presented in Appendix 2. The comparison index is OMX Copenhagen Benchmark GI because no other indices have the complete data from 2002 to 2022. The GI index was specially chosen as it incorporates returns with the cumulative effect of reinvested dividends. The benchmark is partly extracted from Eikon and supplemented with the NASDAQ database since Eikon does not offer monthly returns until May 2003. The prior monthly returns from 2002 June to 2003 May are calculated using the NASDAQ database.

In this study, non-financial firms and firms which have a negative B/M ratio have been excluded. Book values are lagged for 6 months for the availability of information (ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013; FAMA and FRENCH, 1992). Furthermore, other information from financial statements is also lagged for 6 months. Therefore, for the start year of the sample year 2002 June, the prior year, 2001 financial statements are used. In 2002, the data consisted of financial statements of 62 firms, but the number of listed firms gradually increased in the 20-year sample, reaching 111 firms at the end year. Delisted firms and firms not listed for the whole sample period are included to avoid survivorship bias. The most liquid stock series is used if the stock has more than one stock series. In bankruptcies, the return is minus 100%, and delisted firms are sold for their closing price on the last trading date. Databases used are Refinitiv Eikon, Yahoo Finance and NASDAQ, and the analysis was performed using Microsoft Excel 2023 version 16.72.

3.1 Diversification and risk

The firm-specific risk can be spread by adding more stocks to a portfolio. However, it cannot be indefinitely spread with additional stocks since all firms are affected by macroeconomic situations. Firm-specific risk is also called a "unique risk" or "non-systematic" risk, while risk which cannot be lowered is called a "market risk" or "systematic risk". (Bodie, Kane and Marcus, 2021, 194-195) In Appendix 3, the portfolio's volatility is measured by the standard deviation on the y-axis and the number of stocks in the portfolio on the x-axis. As shown in Appendix 3, increasing the number of stocks can lower the standard deviation (unique risk) to a certain unchanging point.

Results from Evans and Archer (1968, 766) prove that most of the firm-specific risk is eliminated with the 8^{th} stock, and to significantly reduce firm-specific further from this portfolio, another 5 stocks is needed, while for a portfolio of 16 stocks, the increase of stocks should be 19 stocks. They concluded that it is questionable whether there is a need to increase portfolio size beyond around 10 securities (Evans, J. L. and Archer, 1968, 767). In contrast to Evans and Archer (1968), Statman (1987) argues that for a stock portfolio to be diversified enough, it should hold a minimum of 30 stocks. Bird and Tippett (1986) note that using actual data, the variance levels for the 10 stocks are higher than what Evans and Archer (1968) used; therefore, to achieve the same level of variance (risk), a portfolio should consist of 22 stocks. Tang (2004, 8) suggested that a portfolio consisting of 20 stocks eliminates 95% of the firm-specific risk, while according to Alekneviciene, Alekneviciute and Rinkeviciene (2012, 345), 22 stocks by capitalization eliminates 97% of the firm-specific risk. Alexee and Tapon (2012, 25) concluded that, on average, 49 stocks are needed to reduce 90% of the firm-specific risk when they studied international markets. Alexeev and Dungey (2015, 1214) concluded that in an equally weighted portfolio, 10 stocks reduced 90% of the firm-specific risk, while 7 stocks reduced 85% of the firm-specific risk when intraday data (5-min, daily and weekly) were used on S&P 500 from 2003 to 2011.

3.2 Enhanced value

Cash-Flow-To-Price (CF/P) tracks the movement of cash into and outside of the firm, and it is favoured by analysts because it is less affected by potential manipulation risk. In other words, some underlying risks could be avoided using CF/P rather than E/P. (Bodie, Kane and Marcus, 2021, 595)

$$CF/P = \frac{Cash\ Flow\ from\ Operations}{Market\ \ Capitalization} \tag{1}$$

EBITDA is calculated with operating income before depreciation and firm Enterprise Value (EV) with equity value plus preferred stock plus equity value and minus cash. EBITDA to EV is calculated by dividing EBITDA by Enterprise Value. Generally, high Enterprise Value firms are an indication for growth stocks (opposite of value), and low Enterprise Value is a character for value stocks. (Loughran and Wellman, 2011, 1629)

$$EBITDA/EV = \frac{Operating\ Income\ Before\ Depreciations}{Enterprise\ Value}$$

(2)

Book-to-Market became widely accepted in the academic environment after Fama and French's (1992; 1993) studies of value premium and the three-factor model, according to Blitz and Haneuer (2020, 64). Fama and French calculated B/M as common equity value plus deferred taxes in the balance sheet for a fiscal year and divided this by market equity (FAMA and FRENCH, 1992, 446). However, the following Formula 3 is used without deferred taxes for this study.

$$B/M = \frac{Common\ Equity\ Value}{Market\ Equity}$$

(3)

Evidence of Net Payout Yield (NPY) was first presented by Boudoukh et al. (2007). Net payout is calculated as dividends plus repurchases minus issues, whereas NPY is net payout divided by yearend market capitalization (Boudoukh, Michaely, Richardson and Roberts, 2007, 11). This study utilises the last year's financial statement market capitalization.

$$NPY = \frac{Dividends + Repurchases - Issues}{Market\ Capitalization}$$

(4)

3.3 Portfolio formation

The size portfolio is formed without any percentile-market cap by handpicking the 10 largest and the 10 smallest firms by market capitalization. The largest firms are incorporated into the "large firm" portfolio, and the smallest firms into the "small firm" portfolio. Each stock is weighted equally; therefore, one stock is 10% of the total portfolio weight. Value portfolio is formed through ranking stocks with CF/P, EBITDA/EV, B/M and NPY, respectively and combining them to total average rank. 10 stocks with the highest combined average value rank are placed in a "high value" portfolio, and 10 stocks with the lowest combined average value rank are followingly placed in a "low value" portfolio. Value ranking is performed on every portfolio when the portfolio is rebalanced each year in June, based on last year's financial statement information. The momentum portfolio consists of 10 firms with the highest 6-month past returns (winners) and 10 with the lowest 6-month past returns (losers). In other words, separate winners' and loser's portfolios are constructed for the whole sample period and rebalanced each year. In the 6-month past return momentum, the most recent month is skipped as it is commonly performed in momentum studies to avoid 1-month reversals. Moreover, the 6-month past return momentum incorporates both price momentum signals and signals from dividends. For all portfolios, a holding period of 1 year is implemented, and each portfolio is rebalanced in June. Formed portfolios and the summary of data used are presented in Appendix 4.

Table 1 presents the correlation matrix of constructed pure-play portfolio returns. As seen in Table 1, high value has a pretty low correlation with the winner portfolio but a significantly higher correlation with the loser portfolio. Combining high-value and winner stocks (value and long-only) could be beneficial as they have little correlation. Another intriguing observation is the negative correlation between winners and small firms, which means that they measure differently and combining them does not increase the risk through co-movement. While both losers and small firms and winners and low value have a negative correlation, it may not be desirable to include firms with low performance in value metrics or firms with poor performance in stock returns. The highest correlation is between the market and the large firm portfolio (0.85), demonstrating their strong link.

Table 1. Formed portfolios correlation matrix of returns

	Market portfolio	*Small firm*	*Large firm*	*High value*	*Low value*	*Winners*	*Losers*
Market portfolio	1,000						
Small firm	0,564	1,000					
Large firm	0,850	0,486	1,000				
High value	0,554	0,665	0,597	1,000			
Low value	0,562	0,468	0,622	0,698	1,000		
Winners	0,435	-0,034	0,247	0,061	-0,008	1,000	
Losers	0,022	-0,203	0,089	0,160	0,461	0,240	1,000

This study will focus on the constructed "pure play" portfolios and their combinations. Mix portfolios are formed by combining pure-play portfolios, commonly used in studying the combination of value and momentum. First, two separate portfolios are constructed and then mixed, utilizing the pure-play portfolio returns (Fitzgibbons, Friedman, Pomorski and Serban, 2017, 3). According to Fitzgibbons et al. (2017), a portfolio that considers both factors together (integrated portfolio) does outperform mix portfolios often; however, in some periods, mix portfolios perform better. Return for a combined portfolio is calculated as pure-play portfolio weight multiplied by its returns (see: ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013). Formula 5 describes how combination portfolio returns are calculated.

$$R_{combination} = w_a * R_a + w_b * R_b \tag{5}$$

Where:

W_a = Portfolio a weight in total combination portfolio

R_a = Portfolio a return

W_b = Portfolio b weight in total combination portfolio

R_b = Portfolio b return

When combining two pure-play portfolios into one combination portfolio, this study will use an equal weight of 0.5, which is often referred to as a 50/50 combination, and some studies suggest that it eliminates liquidity risk while generating much higher returns for value and momentum combination (see: ASNESS, CLIFFORD S., MOSKOWITZ and PEDERSEN, 2013, 939). Therefore, returns for value and momentum portfolios are calculated as 0.5 times value portfolio returns and 0.5 times momentum portfolio returns. These returns are then summed to receive combination portfolio returns. The same procedure applies to other combination portfolios apart from value and momentum long-short strategy, as long-short momentum portfolio returns are calculated 0.5 times long-strategy (i.e., buying winners) and 0.5 times short-selling (i.e., selling losers). Transaction costs nor short-selling costs are not taken into account in this study.

3.4 Models for portfolio returns

3.4.1 Three-factor model

Fama and French (1993) extended the CAPM, identifying other risk factors for stock returns related to the market, firm size, and B/M. The three-factor model is generally accepted for explaining stock or portfolio returns among academics. As reviewed before, both size and B/M have been proven to have predicting power for stock returns, even though the size factor has been struggling in recent years. Fama and French three-factor model is presented in formula format below, on Formula 6.

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB + h_i HML \tag{6}$$

Where:

R_i = Return of an asset

R_f = Risk-free return

α_i = Asset excess return over market return

β_i = Beta of an asset

R_m = Market return

S_i = Beta coefficient for SMB factor

SMB = Size premium (small minus big)

H_i = Beta coefficient for HML factor

HML = Value premium (high minus low)

Fama and French calculated the SMB (size) factor as the difference in average returns between small firm portfolios and large firm portfolios. While HML (value) factor was calculated as the difference in average returns between high-value and low-value portfolios. Furthermore, they suggest that applying value weight can lower variance. (Fama and French, 1993, 9 - 10) This study will not use the three-factor model for determining portfolio returns; however, Fama and French methods of computing SMB and HML factors are applied to examine the performance of the factors.

3.4.2 Four-factor model

Carhart (1997) extended the Fama-French three-factor model with a momentum factor based on the research of Jegadeesh and Titman (1993) on winners and losers to evaluate the performance of mutual funds. While Carhart is credited for forming the four-factor model, more commonly as the name of the fourth factor is used WML, which to the author's best knowledge, is used by Fama and French (2012). Therefore, the four-factor model presented below on Formula 7 is the prevailing form used.

$$R_i - R_f = \alpha_i + \beta_i\left[R_M - R_f\right] + s_i SMB + h_i HML + w_i WML \tag{7}$$

Where:

α_i = Asset excess return over market return

β_i = Beta of an asset

R_m = Market return

R_f = Risk-free return

S_i = Beta coefficient for SMB factor

SMB = Size premium (small minus big)

H_i = Beta coefficient for HML factor

HML = Value premium (high minus low)

W_i = Beta coefficient for WML factor

WML = Momentum premium (winners minus losers)

Fama and French (2012) calculate the WML as the difference in monthly returns between winner and loser portfolios. A similar method for the calculation of WML is used in this study. The beta coefficient is received the same way as for other factors, through linear regression, where market portfolio monthly returns are the independent and the factor returns the dependent variable.

3.5 Portfolio performance and statistical tests

This section examines the evaluation metrics used for portfolios and statistical tests. The first chapter consists of computing methods for raw returns and volatility and describes the statistical tests used to determine the significance of the results. The following chapters describe the risk-adjusted measurements used: Sharpe's ratio, Treynor's ratio and Jensen's alpha.

3.5.1 Returns, volatility and statistical tests

Raw returns portray the performance of portfolio returns when risk-free returns have not been deducted. This study calculates raw returns as monthly averages for each stock. Portfolio returns are calculated for a 1-year holding period by equally weighting individual stocks as 0.1 and multiplying the weight with their corresponding average returns. All portfolios' total average monthly returns are then annualized by multiplying returns with the number of months, thus 12. Monthly returns are also used for the calculation of variance and standard deviation. Variance is computed for each stock monthly, and the monthly average of variance is converted to an average of the monthly total standard deviation by taking a square root of variance. The standard deviation is annualized by multiplying the monthly standard deviation with a square root 12. Noteworthy is that in this study, the variability effects between each stock; in other words, the covariance is not calculated. The previously reviewed standard deviation is used as the primary measurement of volatility.

T-tests were used to test the significance of returns and risk-adjusted returns instead of Z-tests because the sample size was under 30. T-tests are performed as two-sample t-tests assuming unequal variances (Welch's t-test) because the assumption is that they differ in the population. The confidence level of 95% is used for linear regression, and an alpha (p-value) is used to determine the significance of the results. The significance of results is presented with *** if the results are significant with an alpha of 0.01, ** if they are significant with an alpha of 0.05 and * if the results are significant with an alpha of 0.10. Statistical significance for portfolio returns and risk-adjusted returns is analyzed through either p-values or t-Stat, which are received from Welch's t-test. Portfolio beta was computed with regression between monthly and monthly market portfolio returns. Simultaneously, the t-Stat and p-value for portfolio beta and the R^2 values are received with the regression test. Similarly to the p-value, t-Stat describes the statistical significance and is separately presented in the results table. R^2 values explain how well the benchmark explains the returns of portfolios. While it is not a performance metric, it can prove helpful in explaining possible correlations between computed portfolios and the benchmark.

3.5.2 Sharpe's ratio

The most common measurement used for measuring risk-adjusted returns is presumably Sharpe's ratio, which is used to present the excess return of an asset while considering total risk (standard deviation). It was introduced by William Sharpe (1966) and is shown in Formula 8.

$$S = \frac{R_i - R_f}{\sigma_i} \tag{8}$$

Where:

R_i = Portfolio average returns

R_f = Risk-free average returns

σ_i = Portfolio returns standard deviation

The numerator on Formula 8 describes the excess portfolio returns when risk-free returns are reduced from average portfolio returns. As reviewed before, a 3-month Denmark T-bill periodical average return is used for risk-free returns. Consequently, risk-adjusted returns are then divided by portfolio standard deviation to take the risk (volatility of returns) into account. The standard deviation of portfolio returns is computed from the variance of monthly returns. Sharpe ratio should be interpreted as a higher positive number desirable because returns compared to risk taken have been remunerative. In this study Sharpe ratio is calculated similarly to Formula 8, with the addition of annualizing the monthly average Sharpe. The monthly average Sharpe is annualized by multiplying it with a square root of 12.

3.5.3 Treynor's ratio

Another commonly used measurement for risk-adjusted returns is Treynor's ratio, developed by Jack Treynor (1965). Treynor's ratio is calculated in this study as a monthly average and is annualized by multiplying the monthly Treynor's ratio by 12. Similarly to Sharpe's ratio, Treynor's ratio considers risk for excess returns, but instead of total risk (standard deviation), it uses firm-specific risk (beta) (Bodie, Kane and Marcus, 2021, 816). The relationship between risk-adjusted returns and beta is presented in Formula 9.

$$T = \frac{R_i - R_f}{\beta_i}$$

(9)

Where:

R_i = Portfolio average returns

R_f = Risk-free average returns

β_i = Portfolio beta

3.5.4 Jensen's alpha

While Sharpe's and Treynor's ratios describe the relationship between portfolio return and risk, Jensen's alpha presents excess returns compared to CAPM models' predictions. The formation of Jensen's alpha is credited to Michael Jensen (1969). Formula 10 describes the portfolio returns over CAPM, and Alpha is calculated consequently in this study. Jensen's alpha is also computed by averaging monthly Alpha and annualized similarly to Treynor's.

$$\alpha = R_p - [\, R_f + \, \beta_i(\, R_m - R_f)]$$

(10)

Where:

R_p = Portfolio average returns

R_f = Risk-free average returns

R_m = Market portfolio average returns

β_i = Portfolio beta

Jensen's alpha is calculated using monthly averages and therefore annualized by multiplying it by 12. In Formula 10, the excess return is calculated by subtracting risk-free returns from market portfolio returns, multiplied by portfolio beta. This value is then added together with the risk-free rate, and the sum is subtracted from the average portfolio returns.

4 Results

In this section, the results for formed portfolios are presented. In each chapter, the performance of portfolios is shown in table format. Finally, in the last chapter, the results are summarized.

4.1 Firm size

As seen in Table 2, small firms have offered greater average annual raw and cumulative returns than large firms and the market portfolio. However, these results are not statistically significant and within the expected deviation of market portfolio returns. Statistical significance is tested with Welch's t-test, and a confidence level of 95% is used for linear regression; thus, 0.05 alpha implies whether the results are statistically significant. Statistically, results are significant if the alpha is under 0.05 and not significant if the alpha is over 0.05. While returns have been greater for small firms, the volatility (standard deviation) demonstrates that they have not been stable throughout the sample. The annual volatility was much higher for small and large firms, while both were significantly higher than the market portfolio volatility. Both size portfolios outperform the market index portfolio in raw returns.

The underlying risk can also be viewed through beta, which displays the movement of portfolio returns compared to market portfolio movement in returns. A small firm portfolio has a beta of nearly 1.2, meaning that the portfolio's movement is 1.2 times the market movement, whether upside or downwards. The market portfolio beta is 1 because it is used as a comparison and demonstrates the overall market movement. Both betas are statistically significant with an alpha of 0.05, which means that in regression analysis, market returns can explain the returns of both portfolios statistically. In regression analysis, the market portfolio is used as the explanatory variable (independent) and examined portfolio as the explained variable (dependent). R2 is also received through the regression analysis, and while it is not a performance metric, it demonstrates how well the market portfolio returns explain the examined portfolio returns.

When comparing the risk-adjusted returns in Sharpe's ratio, it can be observed that the returns are not as high as they should be for the small firm portfolio as it receives a negative value, which means the small firm portfolio has not created excess returns to risk-free returns when considering total risk (volatility). The market portfolio (0.319) and large firm portfolio (0.179) generate positive Sharpe, while the highest Sharpe generated is on the market portfolio. Meanwhile, Treynor's ratio suggests that a small firm portfolio (0.049) outperforms a large firm portfolio (0.023) and a market portfolio (-0.015) when the risk-adjusted returns are divided by firm-specific risk in the portfolio (beta). When comparing Jensen's alpha, a small firm portfolio (0.207) generates higher excess returns than a large firm portfolio (0.174). All risk-adjusted returns are not statistically significant, meaning that results are within deviations of market portfolio returns. Furthermore, statistical significance demonstrates that these results may not be as reproducible.

Table 2. Size portfolios results

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
Small firm	135,54 %	18,99 %	(0,728)	77,44 %	1,187***	(2,895)	-0,137	(-1,057)	0,049	(0,523)	0,207	(0,744)	0,280
Large firm	129,32 %	15,77 %	(0,576)	41,36 %	1,099***	(6,849)	0,179	(-0,304)	0,023	(0,369)	0,174	(0,501)	0,707
SMB	104,66 %	3,23 %	(-0,946)	10,25 %	0,087	(0,198)	-0,974	(-1,205)	-1,153	(-0,966)	0,033	(-1,068)	0,002

Appendix 5 demonstrates the performance of size portfolios from 2002 to 2022. All portfolios experienced negative returns during the aftereffects of the IT bubble (i.e., 2002-2003) and financial crisis (i.e., 2007-2009), while this impact has been the least for small firm portfolios. However, during COVID-pandemic (i.e., 2019-2020) small firm portfolio was the only portfolio with negative returns. The spikes of small firm portfolios describe the risk of the returns (volatility). However, a high standard deviation caused by the upside movement is not blatantly bad. Therefore, investors who are less risk averse and more prone to more risky stock investments may consider a combination strategy, which includes small firms. With enhancements, the risk of such activity could be enhanced and lowered while receiving a substantial abnormal return above the market returns.

4.2 Enhanced value

Table 3 presents the summary of the enhanced value portfolio results. In cumulative and average annual returns, the difference between high value and low value is astounding. High-value portfolio performed the best with cumulative returns of 140.19% from the start year, while the low-value portfolio generated less returns (106.89%) than the market portfolio (121.22%). In annual returns, similar results were received, while none of the returns were statistically significant. In volatility, it can be observed that with high value, the portfolio's average volatility can be substantially reduced and beta as well. High value receives a beta of 0.637 under the market portfolio beta. Both value portfolios' beta is statistically significant with an alpha of 0.05. In Sharpe's ratio, the high value (0.239) and market portfolio (0.319) both receive a positive value, while the low-value portfolio (-0.201) has a negative Sharpe. Best Sharpe is generated on the market portfolio. In Treynor's ratio, a high-value portfolio

(0.117) outperforms a low-value (-0.079) and market portfolio (-0.014), which both have a negative value. Moreover, in Jensen's alpha high-value portfolio (0.216) performs best. None of the risk-adjusted returns is statistically significant. High value outperforms the market portfolio in returns, beta, Treynor and Alpha, while the market portfolio performs better in volatility and Sharpe.

Table 3. Enhanced value portfolios results

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
High value	140,19 %	20,63 %	(1,366)	36,06 %	0,637***	(2,824)	0,239	(-0,173)	0,117	(0,996)	0,216	(1,126)	0,268
Low value	106,89 %	4,56 %	(-0,768)	63,12 %	1,095***	(2,880)	-0,201	(-1,166)	-0,079	(-0,576)	0,062	(-0,629)	0,277
HML	129,88 %	16,07 %	(0,585)	7,78 %	-0,459	(-1,457)	0,368	(0,585)	-0,062	(-0,244)	0,154	(0,266)	0,056
Market	121,22 %	11,75 %		16,80 %	1,000		0,319		-0,015				

Appendix 6 demonstrates the performance of enhanced value portfolios throughout the sample period. During the 2002-2003 crash, low value and the market portfolio had negative returns, while high value had positive returns. In 2007-2008 all portfolios experienced negative returns, while in 2008-2009, high value shielded from negative impacts and performed nearly 2% annual returns when both the large firm and market portfolio had negative returns.

4.3 Momentum

Table 4 presents the results for momentum portfolios. A long-short portfolio comprises half to buying winners and half to short-selling losers. When examining returns, buying winners has been the most profitable as it generates cumulative returns of 149.09% and average annual returns of 25.24%. The long-short portfolio (120.18%) loses to the market portfolio (121.22%) in cumulative returns, but only slightly. Average annual returns were 11.43% and 11.75%, respectively. None of the returns were statistically significant. While winners may have the highest returns, it has the highest annual volatility (139.30%). The only statistically significant beta was on the winner's portfolio, with an alpha of 0.1. In Sharpe's ratio, all momentum strategies are negative. Therefore, considering the risk (volatility), the returns have not been worthwhile. In this comparison, the market portfolio outperforms all momentum strategies. The long-short strategy performs best when comparing Treynor's ratio (0.423). Noteworthy is that the market portfolio and losers experience a negative Treynor ratio. Meanwhile, in Jensen's alpha, the best-performing portfolio was the winner's (0.271).

Table 4. Momentum portfolios results

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
Winners	149,09 %	25,24 %	(1,077)	139,30 %	1,200*	(2,050)	-0,196	(-1,015)	0,085	(0,815)	0,271	(1,127)	0,144
Losers	102,68 %	2,39 %	(-0,866)	67,53 %	4,156***	(0,095)	-0,220	(-1,205)	-0,078	(-0,588)	0,044	(-0,573)	0,461
WML	151,94 %	27,62 %	(0,899)	22,12 %	1,253	(1,394)	0,652	(0,356)	-1,714	(-0,767)	0,275	(0,794)	0,047
Long-short 50/50	120,18 %	11,43 %	(-0,040)	8,69 %	0,574	(1,659)	-0,205	(-0,450)	0,423	(0,194)	0,114	(-0,219)	0,084
Market	121,22 %	11,75 %		16,80 %	1,000		0,319		-0,015				

Appendix 7 presents the performance of momentum portfolios from 2002 to 2022. During the IT-bubble aftereffects, the winner's portfolio performed the best and the loser's worst. However, the relationship is reversed during the financial crisis as losers generate positive returns. The winner's portfolio has been robust in 2009-2010 and 2019-2020. Interestingly, the loser's portfolio has been quite strong during the COVID-19 rebound, similar to the results of Daniel and Moskowitz (2016), that losers generate returns in the rebound from the bear market. The long-short strategy seems effective in risk minimization as it does not cause negative returns during crashes. However, it does not also generate abnormal returns in growth rallies.

4.4 Factors

Table 5 demonstrates the performance of factors. They are calculated as reviewed before; therefore, annual returns are interpreted as the spread between the constructed portfolios. Furthermore, Mkt-RF cumulative and annual returns are calculated as the market portfolio returns minus risk-free returns. When examining returns, the most potent factor is WML. While SMB is the weakest of the three factors, it outperforms market risk premium. Appendix 8 illustrates the performance of factors. The market risk premium has performed the worst during crises, while interestingly, it has generated positive returns during the COVID-19 pandemic. The poor performance of SMB can be observed, as it either generates inferior returns compared to HML or WML at best and higher negative returns in bear markets.

Table 5. Factors results

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
SMB	104,66 %	3,23 %	(-0,946)	10,25 %	0,087	(0,198)	-0,974	(-1,205)	-1,153	(-0,966)	0,033	(-1,068)	0,002
HML	129,88 %	16,07 %	(0,585)	7,78 %	-0,459	(-1,457)	0,368	(0,585)	-0,062	(-0,244)	0,154	(0,266)	0,056
WML	151,94 %	27,62 %	(0,899)	22,12 %	1,253	(1,394)	0,652	(0,356)	-1,714	(-0,767)	0,275	(0,794)	0,047
Mkt-RF	97,57 %	-1,46 %		16,80 %	1,000		0,319		-0,015				

4.5 Value enhancements

Value and momentum long-only portfolios are formed through a combination of high value and winner's portfolios since buying only winners is regarded as "long-only". Meanwhile, a value and long-short portfolio is formed with half to high value and a half to long-short. In other words, the half to long-short is divided equally by buying winners and short-selling losers. However, noteworthy is that short-selling may not be practical as the loser portfolio contains small firms, which are not generally short-sellable.

Table 6 presents the results for value enhancements. When observing returns, the highest raw returns cumulatively (145.25%) and annually (22.93%) are generated on value and momentum long-only portfolio. Value and momentum long-short is the weakest in returns among the four combination strategies; however, it has the smallest annual volatility (5.19%) and beta (0.605). All betas are statistically significant, with the smallest alpha of 0.01.

Intriguingly all combination portfolios have substantially lower annual volatility and beta than the market portfolio, meaning they are less prone to large market movements. In risk-adjusted returns, value and momentum long-only outperformed all the other portfolios in every category, Sharpe's ratio (1.156), Treynor's ratio (0.100) and Jensen's alpha (0.244). While the difference between value and momentum long-short and value and momentum-long only was not by much in Treynor's ratio. None of these results were statistically significant.

Table 6. Combined value results

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
Value and small firm	138,04 %	19,81 %	(1,049)	8,26 %	0,912***	(3,256)	0,800	(0,424)	0,072	(0,717)	0,211	(0,956)	0,336
Value and large firm	134,75 %	18,20 %	(1,021)	6,02 %	0,868***	(5,560)	0,356	(0,071)	0,058	(0,658)	0,195	(0,834)	0,612
Value and momentum long-short	130,07 %	16,00 %	(0,726)	5,19 %	0,605***	(3,556)	0,539	(0,154)	0,094	(0,435)	0,164	(0,548)	0,380
Value and momentum long-only	145,25 %	22,93 %	(1,436)	8,41 %	0,919***	(3,197)	1,156	(0,720)	0,100	(0,955)	0,244	(1,350)	0,327
Market	121,22 %	11,75 %		16,80 %	1,000		0,319		-0,015				

Appendix 9 describes the performance of combined value portfolios from 2002 June to 2022 June. As seen in Appendix 9, all portfolios experienced negative returns during 2002-2003 from the presumable aftereffects of the IT bubble. However, the market portfolio had substantially higher negative returns than any combination portfolio. During the 2007-2008 financial crisis, value and momentum long-only generated the highest negative returns, and in turn 2008-2009, the market portfolio had the largest negative impacts. Interestingly, in 2008-2009 both value and momentum strategies created positive returns, while other portfolios had negative returns. The rebound from the financial crisis in 2009-2010 is surprisingly manifested more strongly in long-only rather than long-short. Overall, the value and momentum long short may not have the highest spikes, but on the other hand, it does not experience the highest negative impacts during a crisis.

4.6 Summary

Appendix 10 shows the relationship between annual returns and beta for constructed portfolios. Ideally, the portfolio would have the highest average returns possible with the least risk (beta). All combination portfolios have higher returns than the market but with lower beta. Out of the singular strategy portfolios, the high value is the only one which generates higher returns than the market with less risk. Noteworthy is that the long-short portfolio may have lower returns than the market; however, the beta is unexpectedly low. Both losers and low value create exceedingly low annual returns under 5%.

The performance of combination strategies raises the question of whether the performance is enhanced with diversification or by combining two different elements. As reviewed before, having more stocks lowers the firm-specific risk and combination portfolios have, instead of 10 stocks, 20 stocks, which could explain why mix portfolios have similar results.

In Appendix 11, annual portfolio returns are compared with volatility as they may present additional information. As the measurement of volatility, a standard deviation is used. Value and momentum long-only seem to be the best-performing portfolio as it has slightly less than the highest annual returns and nearly the lowest volatility. A pure winner's portfolio generates the highest returns and is not tempting as it has remarkably high annual volatility. Out of the pure strategies, high value performs with the best combination of returns and volatility. Interestingly, it offers a slight edge in both components compared to large firms. Finally, low-value and losers are not viable options because they substantially underperform against the market portfolio in returns and volatility.

Appendix 12 summarises all constructed portfolios and compares them against their peers in their respective categories. Small firms performed the best in cumulative and annual returns in size portfolios, Treynor's ratio and Jensen's alpha. Meanwhile, the large firm portfolio outperformed the small firm in volatility, beta and Sharpe. When examining the value portfolios, high value performed better in each category evaluated, which is similar to the results of Asness et al. (2013).

As shown in Appendix 12, in momentum portfolios, winners generated the highest returns, highest Alpha and best Sharpe, though negative. The long-short portfolio had the lowest volatility and the best Treynor's ratio. Loser's portfolio had surprisingly the lowest beta out of all three momentum portfolios. When examining factors, WML was the strongest and SMB weakest in returns. However, while SMB was the weakest among the three factors, it outperformed against market risk premium (Mkt-RF). In the combination portfolios, value and momentum long-only had the highest raw and risk-adjusted returns (Sharpe, Treynor, Alpha). In turn, value and momentum long short generated the lowest volatility and beta.

Table 7 presents the final comparison of constructed portfolios to review whether the research questions can be answered with the received results. When comparing the high-value portfolio to the market portfolio, it outperforms the market portfolio in raw returns and beta while lagging in Sharpe and annual volatility. Adding a small firm to a high-value portfolio dramatically enhances its performance by decreasing annual volatility from 36.06% to 8.26%, while annual returns also decrease from 20.63% to 19.81%. This enhancement is seen as an increase in Sharpe. Meanwhile, adding small firms increases the beta, lowers Treynor's ratio and slightly the Alpha.

As presented in Table 7, adding momentum to value lowers annual volatility and increases Sharpe on both occasions. Enhancements of value can especially be observed in value and momentum long-only as returns, Sharpe, and Alpha increase while volatility decreases. Drawbacks are higher beta and slightly lower Treynor. When comparing the performance of value and momentum strategies, value and momentum long-only performs better in returns, Sharpe, Treynor and Alpha, while value and momentum long-short has a lower risk in both volatility and beta. Therefore, the value and momentum long-short portfolio is less prone to market movement as it has lower volatility and beta than the market portfolio.

Table 7. Final comparison of portfolios

Portfolio	Cumulative returns (%)	Average annual returns (%)	Return t-Stat	Average annual volatility (%)	Beta	Beta t-Stat	Sharpe	SR t-Stat	Treynor	TR t-Stat	Jensen alpha	Alpha t-Stat	Adj. R2
Small firm	135,54 %	18,99 %	(0,728)	77,44 %	1,187***	(2,895)	-0,137	(-1,057)	0,049	(0,523)	0,207	(0,744)	0,280
Large firm	129,32 %	15,77 %	(0,576)	41,36 %	1,099***	(6,849)	0,179	(-0,304)	0,023	(0,369)	0,174	(0,501)	0,707
High value	140,19 %	20,63 %	(1,366)	36,06 %	0,637***	(2,824)	0,239	(-0,173)	0,117	(0,996)	0,216	(1,126)	0,268
Low value	106,89 %	4,56 %	(-0,768)	63,12 %	1,095***	(2,880)	-0,201	(-1,166)	-0,079	(-0,576)	0,062	(-0,629)	0,277
Winners	149,09 %	25,24 %	(1,077)	139,30 %	1,200*	(2,050)	-0,196	(-1,015)	0,085	(0,815)	0,271	(1,127)	0,144
Losers	102,68 %	2,39 %	(-0,866)	67,53 %	4,156***	(0,095)	-0,220	(-1,205)	-0,078	(-0,588)	0,044	(-0,573)	0,461
Long-short 50/50	120,18 %	11,43 %	(-0,040)	8,69 %	0,574	(1,659)	-0,205	(-0,450)	0,423	(0,194)	0,114	(-0,219)	0,084
Value and small firm	138,04 %	19,81 %	(1,049)	8,26 %	0,912***	(3,256)	0,800	(0,424)	0,072	(0,717)	0,211	(0,956)	0,336
Value and large firm	134,75 %	18,20 %	(1,021)	6,02 %	0,868***	(5,560)	0,356	(0,071)	0,058	(0,658)	0,195	(0,834)	0,612
Value and momentum long-short	130,07 %	16,00 %	(0,726)	5,19 %	0,605***	(3,556)	0,539	(0,154)	0,094	(0,435)	0,164	(0,548)	0,380
Value and momentum long-only	145,25 %	22,93 %	(1,436)	8,41 %	0,919***	(3,197)	1,156	(0,720)	0,100	(0,955)	0,244	(1,350)	0,327
Market	121,22 %	11,75 %		16,80 %	1,000		0,319		-0,015				

5 Discussion

This study aimed to determine whether size, value and momentum effects exist in NASDAQ Copenhagen from 2002 June to 2022 June. In order to support the main research question, four supporting questions were established. The first supporting examined whether the constructed enhanced value portfolio would offer higher returns than the benchmark. As a benchmark, the OMX Copenhagen Benchmark GI index was used. In the second supporting question, the purpose was to find if a combination of small firms would enhance the performance of the value portfolio. The third supporting examined if the momentum factor increases the performance of the value portfolio. Finally, the fourth supporting question inspected if value performs better with a combination of a long-only strategy than a long-short strategy. The financial data (excl., stock price) was downloaded from Refinitiv Eikon as monthly data. Adjusted stock prices were downloaded from Yahoo Finance as monthly data. OMX Copenhagen Benchmark GI was mostly downloaded from Eikon but complemented with the NASDAQ database as it did not include data before 2003. Denmark's

3-month T-bill was fully extracted from Refinitiv Eikon. Financial ratios and statistical tests were computed using Microsoft Excel 2023 version 16.72.

The data consisted of all non-financial stocks corresponding to Fama and French (1992). Book values were lagged for 6 months, similar to a study by Asness et al. (2013). Moreover, values were also lagged for 6 months for other financial statement information. In order to avoid survivorship bias, all firms during inspected sample period were included. Furthermore, this method improved avoiding data snooping as collected data was not pre-modified. Portfolios were formed with 10 stocks due to the small population, though according to Alexeev and Dungey (2015), it lowers the firm-specific risk by 90%. Firm size portfolios were formed using market capitalization and collecting the 10 largest and 10 smallest firms during the inspected year. As for all portfolios, size portfolios were rebalanced each year in June. Such methods offer better statistical reliability as more information is received on the largest and smallest firms' year-to-year.

Value portfolios were constructed using an average ranking method for CF/P, EBITDA/EV, B/M and NPY. A combination of these "sophisticated" value metrics was introduced by Blitz and Hanauer (2020). In the average ranking, 10 stocks with the highest rank were assigned to a high-value portfolio, and 10 stocks with the lowest average rank were assigned to a low-value portfolio. Each year, the average ranking was performed when the portfolio was rebalanced utilizing lagged ratios. Momentum portfolios were formed using the past 6-month return signal, including price and paid dividends. The most recent month was skipped to avoid 1-month reversals, as Grinblatt and Moskowitz (2004) and Asness et al. (2013) suggested. Stocks with the highest past 6-month returns were assigned to the winner's portfolio, and stocks with the lowest past 6-month returns were to the loser's portfolio. 50/50 long-short momentum was computed by combining the winner's and losers' portfolios so that half would be invested in buying winners and half in selling losers.

Notably, as the sample data consists of small-cap stocks, short selling may be impossible to execute in practice for them. Factors were calculated as the difference between two constructed portfolios, suggested in Fama and French's (1993) three-factor model and

Carhart's four-factor model (1997). Lastly, combination portfolios were constructed for value by adding firm size or momentum. Combination portfolios were formed as a 50/50 method using pure-play portfolios (see: Fitzgibbons, Friedman, Pomorski and Serban, 2017). All formed portfolios were evaluated based on raw returns, risk-adjusted returns, and risk. For the measurement of risk-adjusted returns: Sharpe's ratio, Treynor's ratio and Jensen's alpha were used. The risk was measured with beta and annual volatility.

The study results regarding firm size were partly in line with Banz (1981), as small firms generate higher raw and risk-adjusted returns, particularly when measured with a CAPM-based model (e.g., Jensen's alpha). Furthermore, this study extended the risk-adjusted metrics to Treynor's and Sharpe's ratios. The small firm portfolio performed better when returns were adjusted with firm-specific risk (beta). However, the small firm portfolio generated a negative Sharpe when measuring Sharpe's ratio. In contrast, the large firm portfolio generated a positive value, which is due to the much lower annual volatility of the large firm portfolio. In conclusion, it can be stated that a size premium exists in NASDAQ Copenhagen from June 2002 to June 2022 as small firms generate higher annual and cumulative returns and, with some metrics, higher risk-adjusted returns. However, in line with Alquist et al.'s (2018, 44 - 45) results, Denmark has no statistically reliable size effect when examining the t-Statistic.

When examining the high-value portfolio compared to the market portfolio, it generated higher cumulative and annual returns, lower beta and better Treynor's ratio. However, the market portfolio had significantly lower annual volatility and a better Sharpe ratio. With these results, it cannot be concluded that the enhanced value portfolio would outperform the market portfolio due to the differences presented. Both portfolios have their merits in different categories, and the selection depends on the individual investor's preferences.

This study produced similar evidence as the results of Blitz (2020, 61) from ex-US, where WML performs the best, HML second best, and SMB is the weakest in returns. Whilst our findings indicated a more robust performance (3.23%) of the SMB factor for the whole sample period, compared to the SMB performance from 2010-2019 (1.38%) in Blitz's study, however, it is closer to the performance of the SMB from 2000 to 2009 (3.57%) (Blitz, 2020, 62). Meanwhile, compared to Foye's (2016, 227) evidence from Denmark, our results suggested more robust performance for SMB, WML and HML, though not statistically significant. The more robust performance of HML could be explained using a composite ratio.

While Asness, Moskowitz and Pedersen (2013) utilized the past 12-month returns as the momentum signal and did not have a composite value in their study, this study produced partly similar results. Raw returns and Sharpe ratio increased, and volatility decreased with the combination of value and momentum (long-only). The difference between this study and Asness et al. (2013) is that in our results, Jensen's alpha increased for the value and momentum long-only combination. The author acknowledges that this could be due to including the very smallest firms and not including the percentile market cap. The other explanation could be the differences in the inspected period, market and the more comprehensive value measurement with a composite ratio. Furthermore, risk-adjusted measures were extended in this study to Treynor's ratio, where a high-value portfolio performed better than the combinations of momentum and value. In conclusion, the momentum effect exists in OMX NASDAQ Copenhagen from June 2002 to June 2022, while it is stronger on the winner's side. Moreover, the combination of value and long-only offers tempting benefits to pure value, which include higher returns, Sharpe, Alpha, and lower volatility. In contrast, the downsides include a lower Treynor's ratio and higher beta.

Finally, to answer the fourth supporting question, whether long-only performs better than long-short together with value. When comparing risk-adjusted returns, value and momentum long-only outperformed value and momentum long-short in Sharpe, Treynor and Alpha. Raw returns and cumulative returns were higher for value and momentum long-only, while value and momentum long-short had lower beta and lower volatility. Nonetheless, it cannot be with certainty stated that the value and momentum long-only strategy is outrightly better than the value and momentum long-short strategy due to higher volatility and beta; for risk-averse investors long-short strategy might seem like a viable option to minimize risks while outperforming the overall market. Investors more comfortable with the risk may consider a combination of value and momentum long-only strategy as it has higher raw and risk-adjusted returns and presumably lower transaction costs.

5.1 Conclusions

Based on the results of this study, investors might want to avoid firms with low CF/P, EBITDA/EV, B/M and NPY and loser firms as they performed much worse than the market portfolio. In conclusion, an enhanced value portfolio can be improved further by adding firm size or momentum, while the improvements are more evident with a long-only strategy. Adding a long-only strategy to a composite value portfolio increases risk-adjusted returns and lowers volatility. While not all enhancements improve the returns of the composite portfolio, they all lowered the annual volatility under the market portfolio volatility. With enhancements, no single best option is presented as the returns and risks vary. However, the critical takeaway from the results should be interpreted as a more extensive toolkit for investors or academics to observe different portfolio choices and their strengths. Finally, the results presented in this study are not to be taken as investment advice.

When observing the results, the limitations and scope of the study should be noted. This study used a 1-year holding period and 6-month past returns, whereas including different holding periods, momentum signals, and composite values could very well produce different results. Additionally, including the very smallest firms in the sample could have impacted the results of the long-short strategy as, in practice, small-cap firms are not generally short-sellable. Lastly, this study did not include transaction costs, short-selling or taxes, and their inclusion could significantly impact the results, particularly on the long-short strategy.

5.1 Validity, reliability, and future research

In this chapter, the validity and reliability of the study are critically reviewed. According to Heale and Twycross (2015), in quantitative studies, the validity portrays how precisely the study captures the measured phenomenon. They divide the validity into three elements: 1. Content validity, 2. Construct validity, and 3. Criterion validity. In content validity, it is examined whether the instrument measures all the aspects of the phenomenon. In construct validity, it is viewed if deductions can be made based on the results. Finally, a criterion is an alternative instrument that measures the same phenomenon, and correlations are used to determine how strong each instrument is with the measured phenomenon. (Heale and Twycross, 2015, 66)

Therefore, the content validity can be reviewed for firm size, value, and momentum. For the measurement of firm size, market capitalization was used. Market capitalization captures the firm size well, as small firms have fewer stocks than large firms since small firms are less popular, and thus there is less demand for the stocks of small firms. The value was measured using a composite ratio, where each ratio was a characteristic of a value firm, based on extensive evidence. Similarly, the momentum utilizing previous research used a return and a dividend signal of the past 6 months. Criterion validity can be measured with convergent and divergent validity, where for the first, the correlation between instruments is strong, and for the latter, it is weak (Heale and Twycross, 2015, 66). Heale and Twycross suggest that a correlation above 0.5 depicts a strong, while under 0.3 is weak (Heale and Twycross, 2015, 67). Divergent validity can be observed in the Table 1 correlation matrix; some formed portfolios have a strong correlation (above 0.5), meaning they partly measure the same phenomenon. Therefore, the co-movement cannot be avoided in some portfolios, thus lowering the validity.

Reliability depicts the measurement methods' consistency when used repeatedly (Heale and Twycross, 2015, 66 - 67). The study's validity and reliability improved due to a long sample period of 20 years since it includes different market conditions, from major crises to growth rallies. Moreover, measuring the market anomalies in a 20-year sample from year-to-year increases the validity of capturing them more precisely. Furthermore, including dividend-adjusted monthly stock prices and a dividend-adjusted benchmark produces a more realistic view and improves validity. In turn, the lack of other benchmarks lowers the validity of results, as other market indices could have been better at describing the market returns.

Furthermore, this affects the reliability of the calculations where market portfolio returns are used. However, to the author's best knowledge, one does not exist.

Extremely small firms could produce abnormal results due to their infrequent trading, though according to some studies, it does not explain the size effect (Stoll and Whaley, 1983). However, in our view, illiquidity causes high volatility in trading. Furthermore, it might explain why returns and risk-adjusted returns were not statistically significant together with the limitation of 10 stocks in a portfolio. The reliability could have been enhanced by calculating a percentile cap for market capitalization and including only the most liquid stocks. Most liquid stocks could have been chosen as the top 20% – 30% or the bottom 20% – 30%.

Moreover, increasing the number of stocks in a portfolio from 10 to 20-25 could have improved the statistical significance of the results. However, the lack of firms in the sample data lowered the reliability as there were only 62 firms listed at the start year, while it did increase at the end year to 111 firms. In order to ensure the consistency of used metrics, statistical tests were used to find whether the results were statistically significant. The chosen tests were linear regression and Welch's t-test, which are easily reproducible for the data. Furthermore, the reliability increases for a risk-free rate as the 3-month Denmark T-bill rate is used as monthly average returns yearly rather than an average of the whole 20-year period.

Applying all the improvements reviewed before with different holding periods and momentum signals seems intriguing, as the relationship between value and momentum requires more attention in different valuation metrics. It is known that the holding period significantly enhances value performance when extending it. However, to capture the best performance of momentum, such a holding period might not be as suitable. Furthermore, the performance of NPY is often neglected in research, and D/P is often used in composite ratios, even though repurchases have become prevalent. Moreover, as reviewed before, region-wide samples could significantly affect size and momentum signals, thus delivering results that may not describe the effects at the more fundamental level. Therefore, further evidence of Nordic equity markets at the country-specific level is needed.

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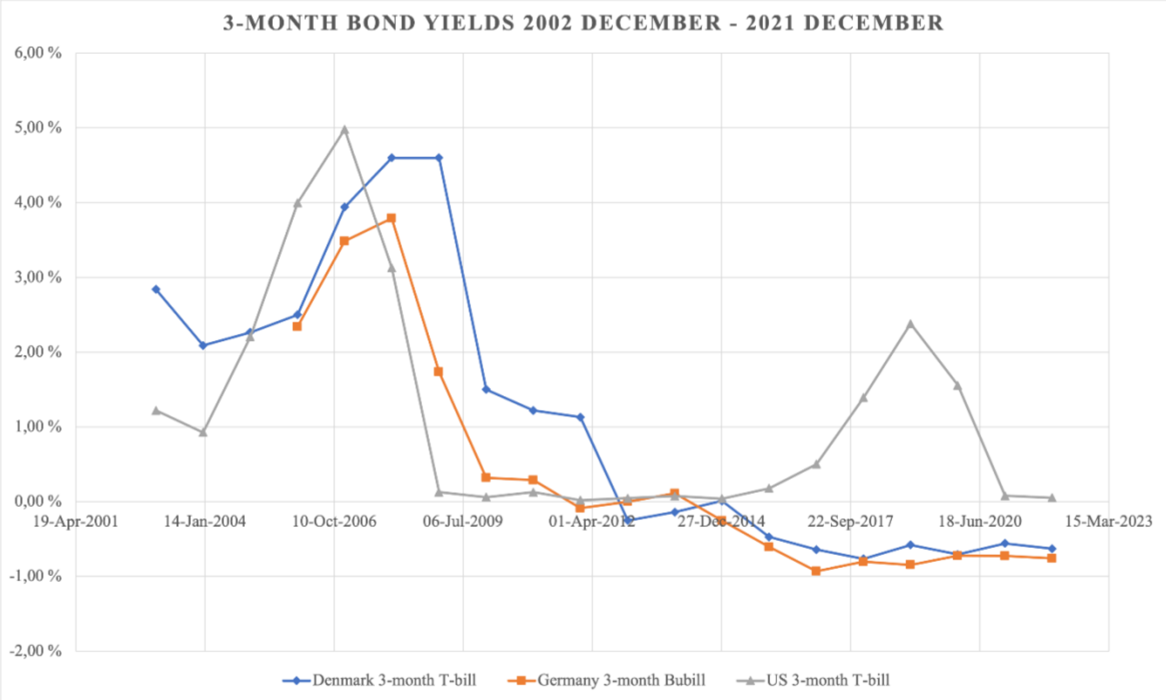
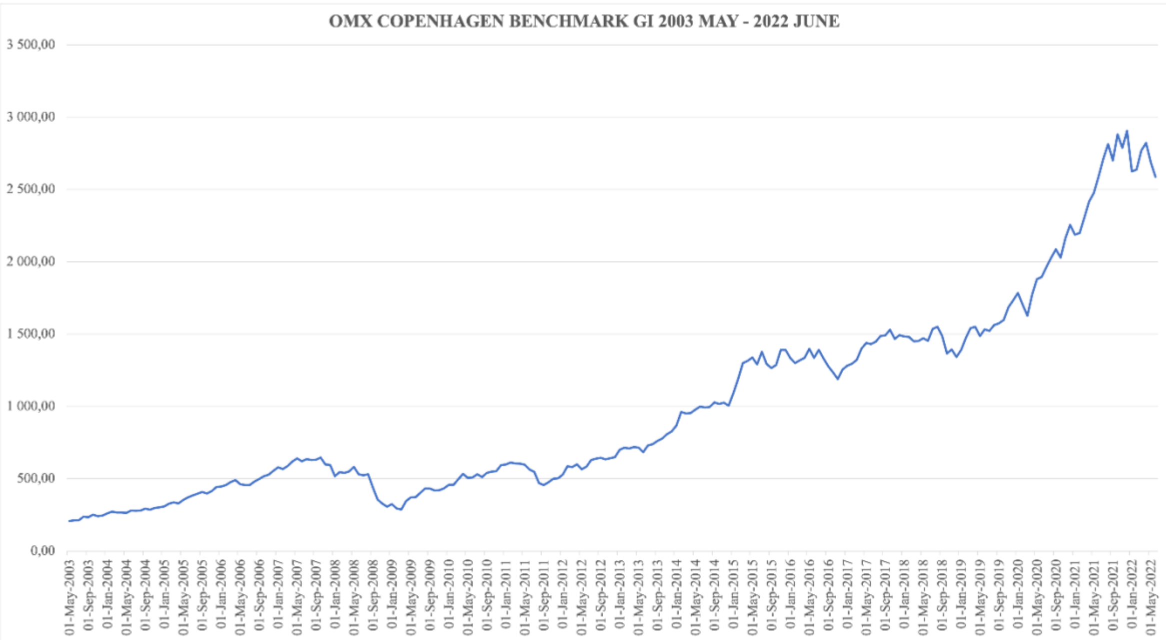
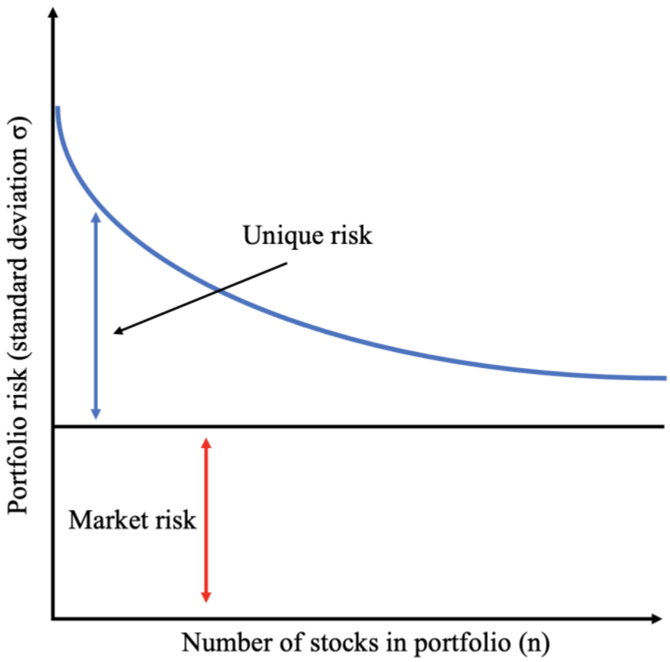
Appendix 1. 3-month bond yields



Appendix 2. OMX Copenhagen Benchmark GI



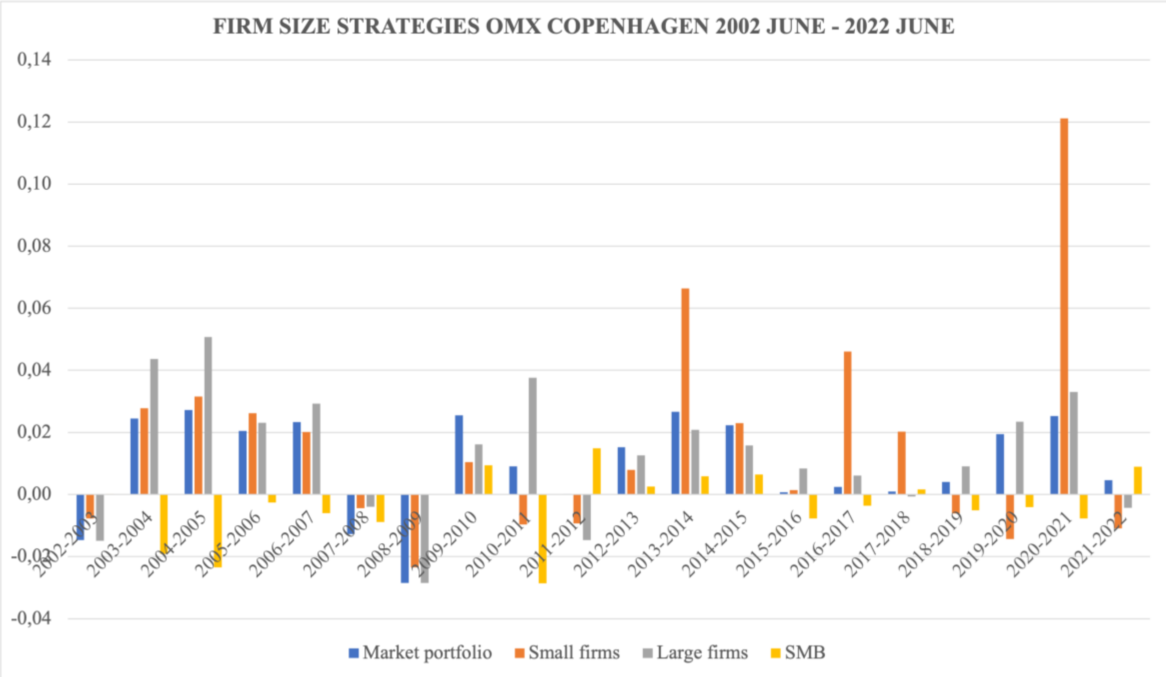
Appendix 3. Portfolio diversification and risk



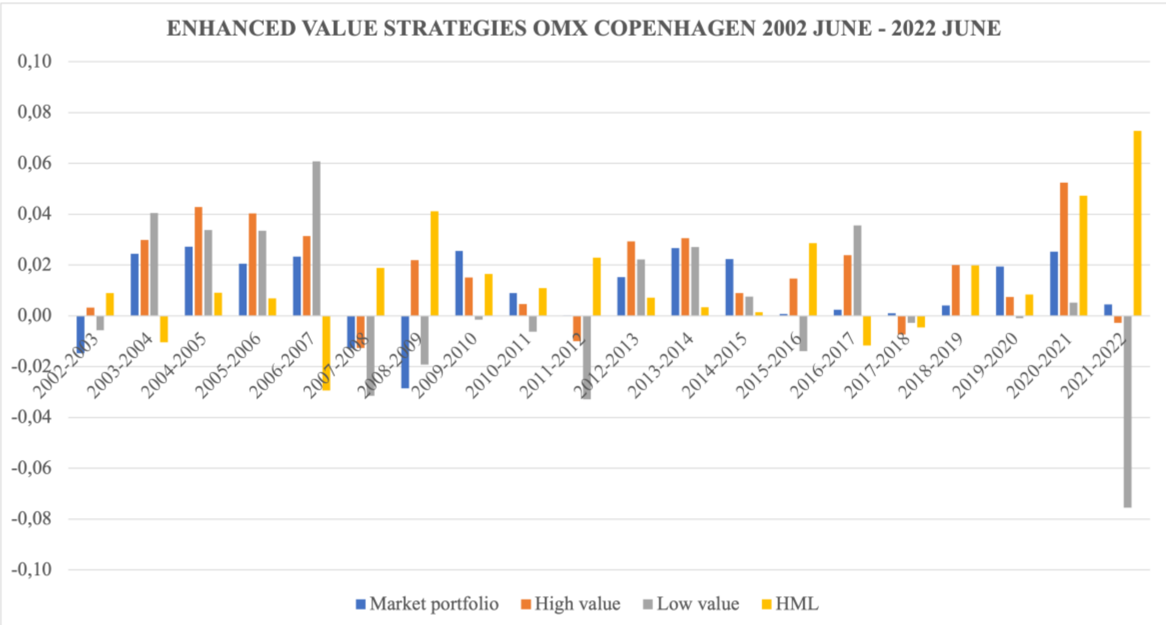
Appendix 4. Summary of formed portfolios

	Small firm portfolio	**Large firm portfolio**	**High value portfolio**	**Low value portfolio**	**Winners portfolio**	**Losers portfolio**
Number of stocks in portfolio	10	10	10	10	10	10
Number of portfolios	20	20	20	20	20	20
Total number of stocks	200	200	200	200	200	200
Total number of individual firms	31	19	45	60	77	88
Total number of financial data (excl. share price)	200	200	800	800	200	200

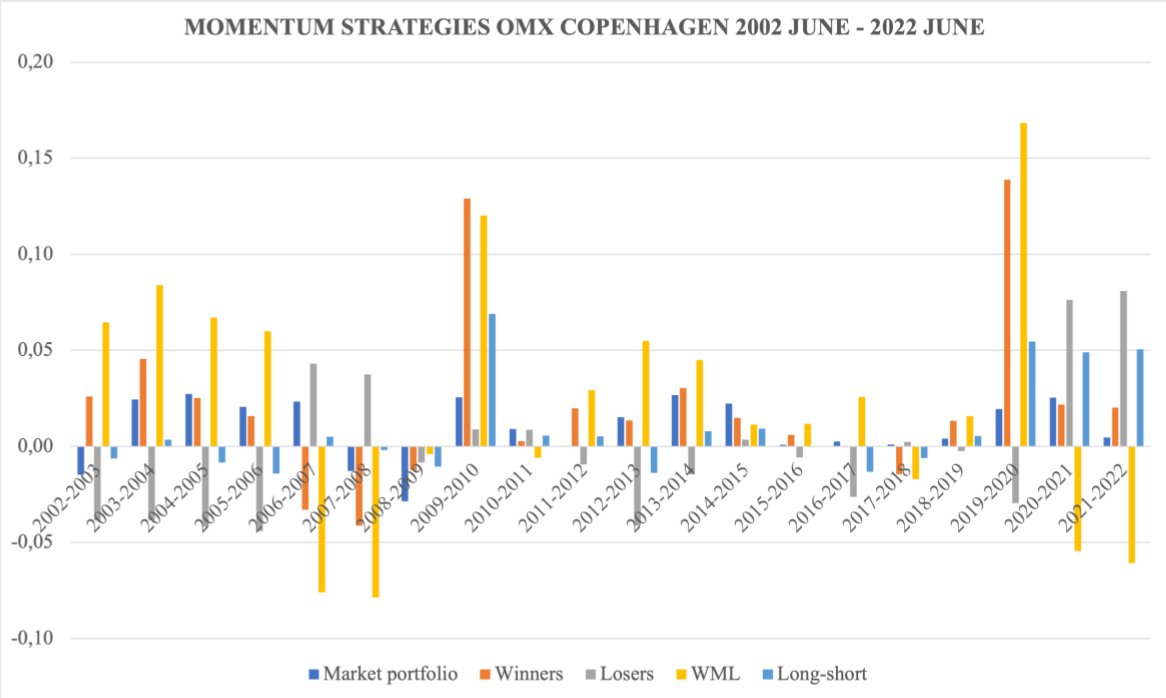
Appendix 5. Performance of firm size strategies



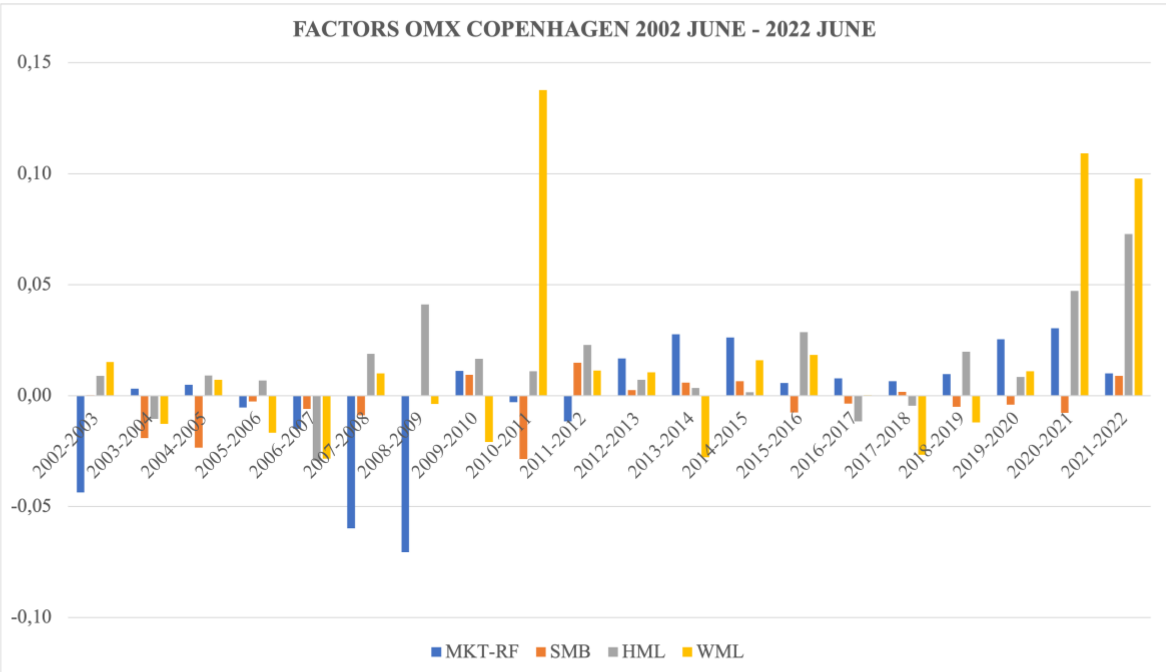
Appendix 6. Performance of enhanced value strategies



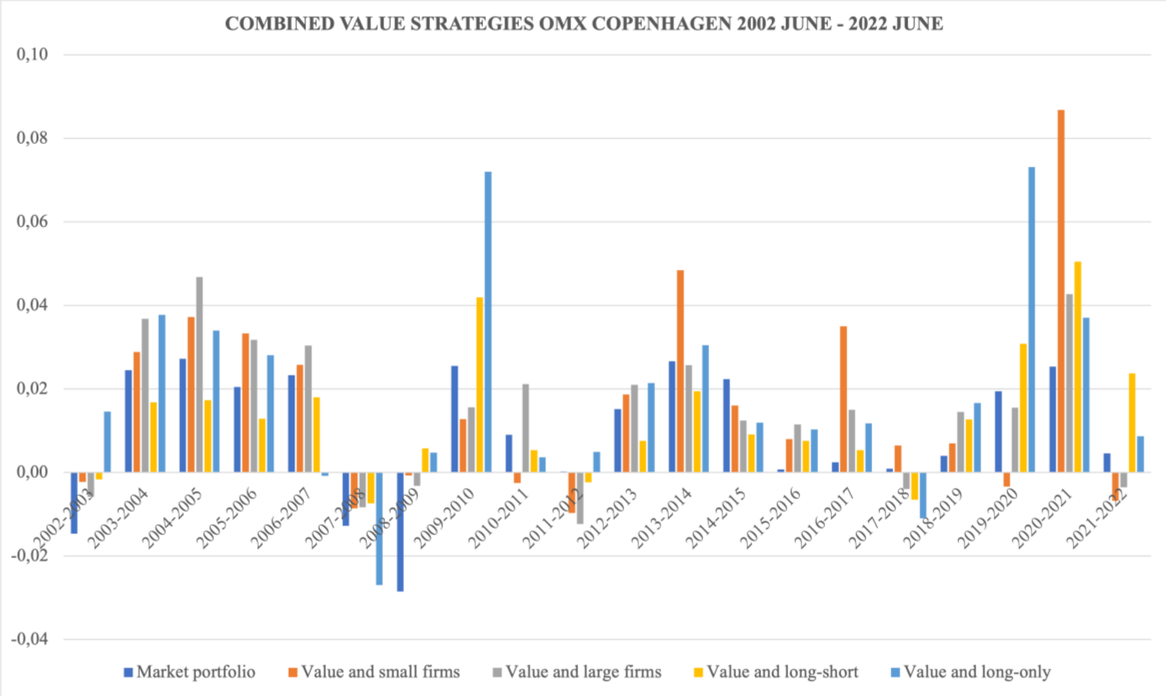
Appendix 7. Performance of momentum strategies



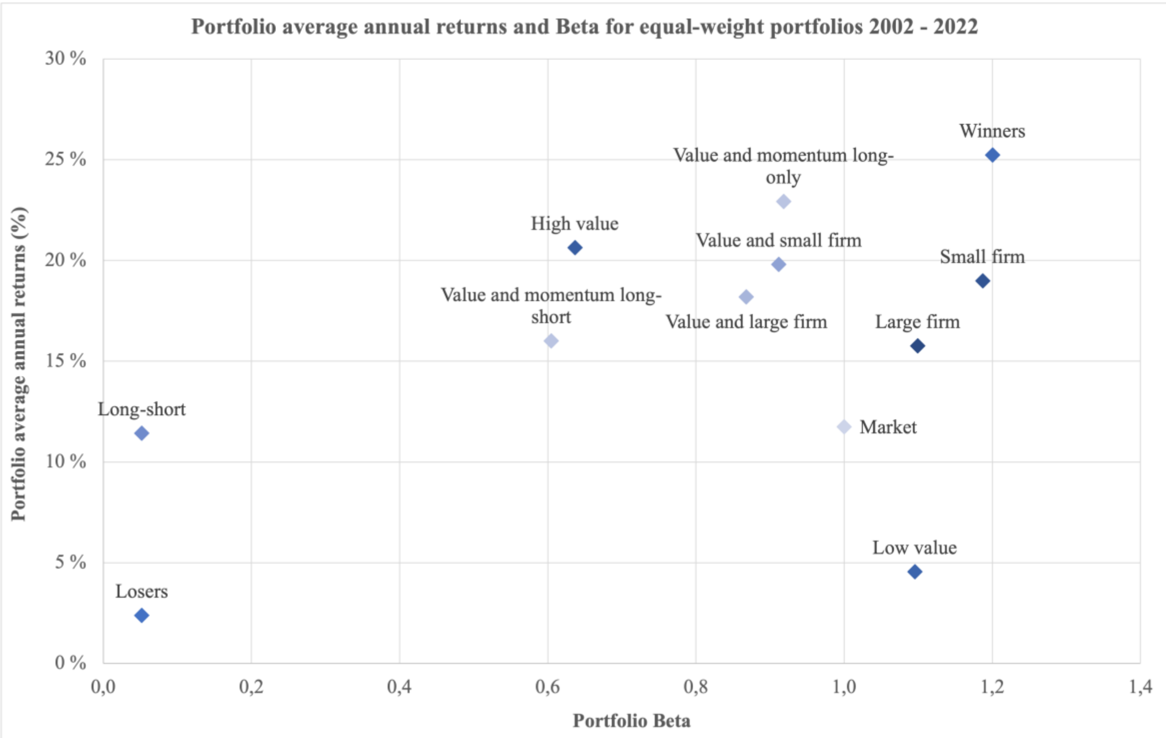
Appendix 8. Performance of factors



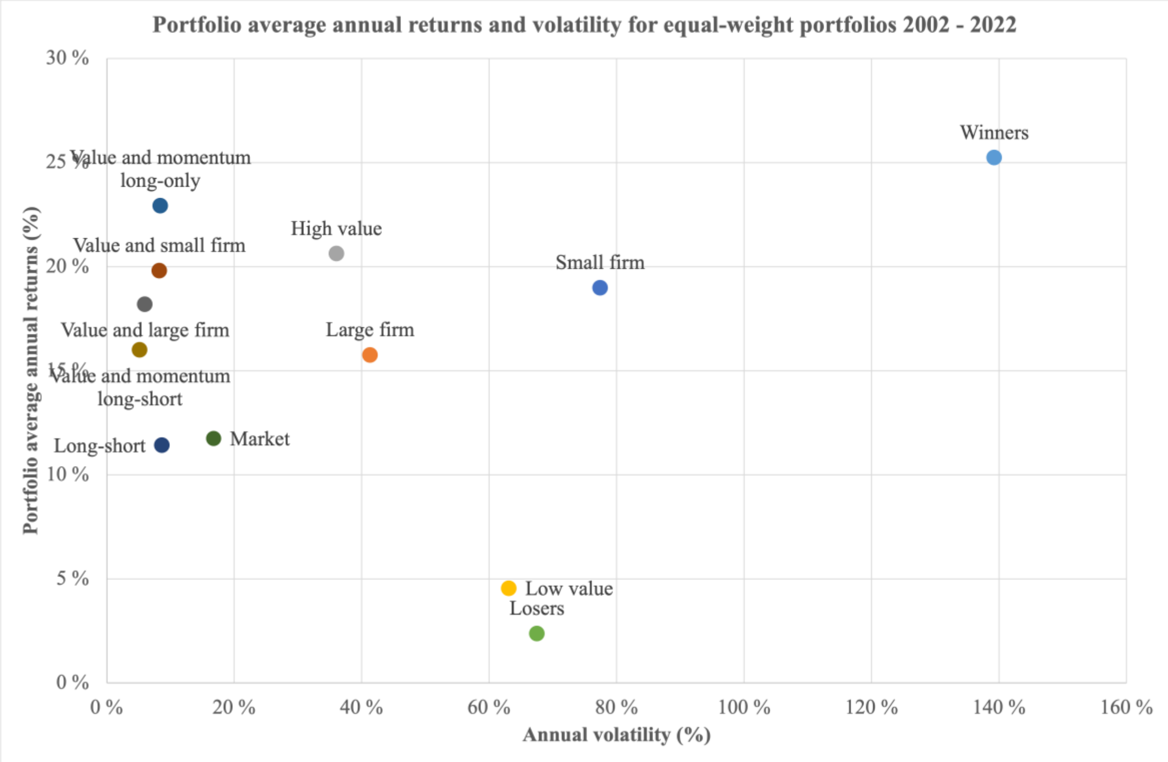
Appendix 9. Performance of combined value strategies



Appendix 10. Portfolio returns and beta



Appendix 11. Portfolio returns and volatility



Appendix 12. Summary of results

Portfolio	Cumulative returns	Average annual returns	Average annual volatility	Beta	Sharpe	Treynor	Jensen alpha
Size	Small firms generated higher cumulative returns	Annual returns higher for small firms	Large firms lower volatility than small firms	Large firm portfolio better beta than small firms	Large firms better Sharpe than small firms	Both had positive Treynor's compared to market portfolio negative. Best in small firms.	Small firm portfolio highest alpa.
Value	High value portfolio generated nearly 40% higher cumulative returns than low value.	Annual returns were nearly five times higher in high value, compared to low value.	High value portfolio had significantly lower annual volatility.	High value lower beta than market.	High value positive Sharpe, negative for low value.	High value positive Treynor, low value negative.	Both had positive alpha. Substantially higher for high value.
Momentum	Winners portfolio highest cumulative returns and second best in long-short.	Winners highest.	Long-short portfolio remarkably low volatility. Losers second best.	Losers best beta and long-short second best.	All momentum strategies negatie Sharpe. Winner's least.	Long-short best Treynor, which is significantly higher than in Winner's.	Highest alpha on Winner's portfolio and second highest long-short.
Factors	Highest performance in WML. SMB weakest, but better than market.	Similar ranking as in cumulative returns. Best WML, second best HML and weakest SMB.	HML lowest and SMB second lowest. WML highest.	HML negative. SMB and WML both positive, while WML highest.	WML highest and HML second highest. SMB negative and worse than market.	HML least negative, highest negative value for WML.	WML highest and HML second highest. SMB worst. All value positive.
Combination	Value and momentum long-only highest and value and momentum long-short weakest. Long-short better than market.	Similar results as in cumulative returns. Value and momentum long-only best and value and small firms second best.	Value and momentum long-short lowest volatility and value and large-firm second best. Highest value and momentum long-only.	Lowest in value and momentum long-short, highest for value and momentum long-only. All values under market beta.	Value and momentum long-only best and value and large firm lowest. All combinations outperformed market.	Highest value and momentum long-only, second best value and momentum long-short. All values positive and better	Value and momentum long-only highest, value and momentum long-short lowest. Second best value and small firms.