LUT School of Business and Management

Bachelor's thesis, Business Administration

Strategic Finance

Investigating the performance of a value-momentum strategy employing EBIT/EV valuation multiple and 3-month momentum indicator in Nasdaq Helsinki between 2010-2020

EBIT/EV arvostuskertoimen ja 3 kuukauden momentum indikaattori yhdistelmäportfolion suoriutuminen Nasdaq Helsinki pörssissä 2010–2020 aikavälillä

28.08.2020

Author: Dani Porkka

Supervisor: Maija Hujala

ABSTRACT

Author:	Dani Porkka
Title:	Investigating the performance of a value-momentum strategy employing EBIT/EV valuation multiple and 3-month momentum indicator in Nasdaq Helsinki between 2010-2020
School:	School of Business and Management
Degree programme:	Business Administration, Strategic Finance
Supervisor:	Maija Hujala
Keywords:	Value-momentum, Momentum, Value, EV/EBIT, Value investing, Momentum investing

The purpose of this thesis is to examine the performance of a value-momentum combination portfolio in Nasdaq Helsinki between 2010 - 2020. The value indicator employed in the study is EBIT/EV, and the employed momentum indicator is 3-month momentum. Portfolios are composed using ranking and average ranking. The effect of the inclusion of a 3-month momentum indicator in an EBIT/EV value portfolio is investigated using different risk-adjusted performance measures. The programming language R is utilized in the calculations, statistical testing, and data-analysis. This study extends the finance literature on the use of the inverse EV/EBIT valuation multiple and 3-month momentum in portfolio formation. The added value from momentum in EBIT/EV value portfolio is documented in addition to the persistence of value and momentum anomalies in Nasdaq Helsinki.

TIIVISTELMÄ

Tekijä: Dani Porkka

Tutkielman nimi: EBIT/EV arvostuskertoimen ja 3 kuukauden momentum indikaattori yhdistelmäportfolion suoriutuminen Nasdaq Helsinki pörssissä 2010–2020 aikavälillä

Akateeminen yksikkö: LUT-kauppakorkeakoulu

Koulutusohjelma: Kauppatieteet, Strateginen rahoitus

Ohjaaja: Maija Hujala

Hakusanat: Value-momentum, Momentum, Value, EV/EBIT, Value investing, momentum investing

Tämän tutkielman tarkoituksena on tutkia EBIT/EV arvostuskertoimen ja 3 kuukauden momentum indikaattorin yhteisvaikutusta Helsingin pörssissä 2010–2020 aikavälillä. Portfolioiden muodostamisessa on käytetty arvonmukaista järjestelyä ja arvonmukaisen järjestelyn keskiarvoa. Portfolioiden suoriutumista on mitattu useammalla riskikorjatulla mittarilla. Tuloksien ja tilastollisten testien laskemisessa sekä datan analysoimisessa on hyödynnetty R ohjelmointikieltä. Tutkimus laajentaa rahoitukseen keskittyviä tutkimuksia, jotka käsittelevät EBIT/EV arvostuskertoimen ja 3 kuukauden momentum indikaattorin käyttöä portfolioiden muodostamisessa. Tutkimuksen tuloksista selviää, että momentum indikaattorin ja EBIT/EV arvostuskertoimen yhteisvaikutuksesta syntyy lisäarvoa. Tuloksien perusteella arvo ja momentum anomaliat ovat edelleen läsnä Nasdaq Helsinki pörsissä.

TABLE OF CONTENTS

LIST OF APPENDICES

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Various investment strategies utilizing value and momentum in the hopes of outperforming the stock market have been popular among finance researchers and practitioners in the past decades. These stock market anomalies as investment strategies have historically generated excess returns in various stock markets, thus challenging the efficient market hypothesis. In the light of prior academic research, both value and momentum investment strategies have enabled investors to gain excess returns (for example see Fama & French 1992, 2006; Jegadeesh & Titman 1993, 2001; Chan, Jegadeesh & Lakonishok 1996). Since the academic literature shifted its attention to momentum returns, the strategy of combining value and momentum indicators has been studied in several markets with a variety of combinations (for example see Bird & Casavechia 2007; Brown, Rhee & Zhang 2008; Fisher, Shah & Titman 2016; Groby & Huhta-Halkola 2019; Huang, Zhang, Zhou 2017; Leivo & Pätäri 2011).

When investigating value-momentum combination portfolio performances in the Nordic equity markets, Grobys and Huhta-Halkola (2019, 2875, 2881) found that value-momentum strategies increased Sharpe ratios and offered investors diversification benefits between 1993-2017. Similarly, Leivo and Pätäri (2011, 407) found strong evidence that price momentum in conjunction with single or composite relative valuation multiples would have added value to investors in Nasdaq Helsinki, formerly known as the Finnish Stock Exchange, between 1993-2008. Furthermore, Huang et al. (2017, 32) found that a combination strategy utilizing a factor constructed from seven firm fundamental value trends enhanced with price momentum could have provided investors excess returns; the combination strategy retrospectively returned more than twice the return of a traditional price momentum strategy without increasing risk. While the method employed by Huang et al. (2017) does not relate to value investing directly, it provides evidence of gaining excess returns by combining valuation multiples with price momentum.

The corroborative two-way relationship of value and momentum was also documented by Fisher et al. (2016, 46), who found the integration of a value strategy in a

momentum portfolio to increase returns, even in a period where momentum had performed poorly. Furthermore, Grobys and Huhta-Halkola (2019, 2882) and Huang et al. (2017, 32) found combination strategies to increase the performance of pure-play strategies; strategies utilizing value or momentum alone. Conversely, Bird and Casavecchia (2007, 243) found the sole inclusion of price momentum to add little to the performance of a long-only value strategy in the European equity markets in the 1989-2004 period. However, Bird and Casavecchia (2007, 244) found the inclusion of an acceleration indicator in conjunction with price momentum to help in recognising lasting price movements from short performance bursts, thus enabling better timing of entry into value stocks and earning higher returns. Interestingly, Asness (1997, 34) found the connection between value and momentum to be conditional and negatively correlated, which implied that buying firms considered good momentum stocks entailed pursuing a poor-value strategy, and vice versa. The explanations for returns from value, momentum and value-momentum investment strategies is still under debate to the best of my knowledge.

1.1 Aim and research questions

Prior studies have illustrated that value-momentum strategies could have provided investors with excess returns. However, the combination of earnings before interest and taxes-to-enterprise value (henceforth referred to as EBIT/EV) relative valuation multiple and 3-month price momentum has not been studied in the context of Nasdaq Helsinki in the 2010-2020 period. Furthermore, the relevance of studying EV/EBIT multiple in conjunction with price momentum is supported by a suggestion for further research by Grobys and Huhta-Halkola (2019, 2882). Additionally, the results of Pätäri, Karell and Luukka (2016, 83) motivates the use of EBIT/EV multiple as a value indicator, since from single valuation multiples it provided highest excess returns in the Finnish Stock Exchange over the 1996-2013 period. A simple method for composing combination portfolios is employed in this study to investigate the performance of the discussed combination strategy.

The aim of this study is to investigate the performance of a long-only portfolio utilizing a combination of EBIT/EV value indicator and price momentum in Nasdaq Helsinki using a sample period from May 2010 to May 2020. Furthermore, pureplay value and

momentum strategies are investigated in the bounds of the scope of the study to illustrate, whether the value-momentum combination portfolio can outperform the mentioned pureplay strategies. Two research questions answered in this study are the following:

RQ1: "*How the employed value-momentum combination investment strategy has performed in Nasdaq Helsinki during the 2010-2020 period?*"

RQ2: "*What is the difference in performance between the value-momentum and the pureplay investment strategies?"*.

1.2 Scope, limitations, and structure

The scope of this study places several limitations on investigating the discussed combination portfolio returns. First, transaction costs are not considered in this study, even though they have a negative effect on portfolio returns (see for example Barroso & Santa-Clara 2015; Brandt, Santa-Clara & Valkanov 2009; Grundy & Martin 2001). Second, the effect of firm size on the returns is not tested, despite many arguments that it could explain returns originating from value investing strategies (See for example Basu 1983; Fama & French 1992, 2015; Bird & Whitaker 2003; Grobys & Huhta-halkola 2019). Third, the implementation of a more sophisticated asset pricing model in explaining returns of the employed investment strategy is left outside of the study as a subject for future research (see for example Carhart 1997; Barillas & Shanken 2018; Daniel, Hirshleifer & Sun 2017; Fama & French 1992, 2015, 2018; Hou, Xue & Zhang 2015; Hou, Mo, Chen & Zhang 2018, 2019). Fourth, the effect of different holding periods and determining optimal holding periods for value and momentum stocks are outside the scope of this study. Lastly, an explanation for possible combination portfolio returns are not investigated.

The data employed in the study is very context bound since only Nasdaq Helsinki is investigated. Furthermore, the small amount of observations from the elimination of financial stocks and the limiting stock universe of including only publicly listed companies reduces the sample size. These sample related constraints may limit generalizations from the results and findings. Hence, the study attempts to provide

information on the performance of the combination strategy explicitly in the bounds of Nasdaq Helsinki.

The remainder of the study is organized as follows. The next section introduces the theoretical background of factors related to the value-momentum combination strategy. Value strategies, momentum strategies and the EBIT/EV valuation multiple are discussed including possible explanations suggested by academic literature for the excess returns for each mentioned strategy individually. The third section outlines the data and research methods employed. The fourth section illustrates the empirical results of the study. The last and conclusive chapter summarizes the findings of the study and proposes suggestions for future research.

2. THEORETICAL BACKGROUND

Lakonishok, Shleifer and Vishny (1994, 1541) describe value investing strategies as buying stocks with relatively low prices compared to measures of value. Value investing strategies aim to find under-priced stocks by determining an intrinsic value for stocks and utilizing relative valuation multiples to evaluate stock valuations compared to company peers. Hence, value investors buy cheap stocks and sell expensive stocks based on value determined by different valuation tools. The excess returns stemming from the overperformance of relatively cheap stocks based on valuation multiples is often referred to as the value premium by academic literature. According to Chen, Petkova and Zhang (2008, 269) the value premium is calculated by comparing stock returns based on their valuation multiples; the premium is calculated by subtracting the average return of relatively expensive stocks from the average return of relatively cheap stocks.

The value premium has been investigated by prior academic research and the results suggest that retrospectively investors could have achieved excess returns in various stocks markets by employing value investing strategies. Fama and French (1992, 450) identified a value premium for the 1963-1990 period in the U.S. stock market for stocks with a high book value of equity-to-market value of equity. Later, Fama and French (2006, 2183) found that earnings-to-price and book-to-market value produced strong value premiums in both the U.S. stock market in the 1963-2004 period and in 14 major

markets outside of the U.S. in the 1975-2004 period. The findings are also supported by Lakonishok et al. (1994, 1574), who found that value strategies utilizing various valuation multiples outperformed in the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) between the 1964-1990 sample period. Furthermore, Bird and Whitaker (2003, 245) reported value investing strategies employing book-to-market and sales-to-price to overperform despite considering the effect of size to the returns in the major European markets in the 1990-2002 period.

2.1 The size effect

The effect of market capitalization on stock returns, also known as the size effect, has been suggested to be an explanatory factor for the excess returns from value investing strategies and the value premium. Banz (1981, 6, 17) reported small capitalization NYSE stocks on average to have higher risk-adjusted returns compared to large capitalization NYSE stocks in the 1926-1975 period. Furthermore, Basu (1983, 24) reported small capitalization stocks to outperform large capitalization stocks in NYSE between 1962-1979 and suggested that the size effect was a separate explanatory factor rather than a proxy.

Later, Fama and French (2015, 3) reported higher returns for small capitalization stocks with a high book-to-market value of equity using only NYSE quintile breakpoints with a sample composed of the U.S. stock market in the 1963-2013 period. Authors in prior research have considered the effect of company size to explain returns from employed value strategies. For example, Bird and Whitaker (2003, 245) reported the effect of firm size to reduce excess returns from the value strategy employed by the authors across major European markets over the 1990-2002 period. Moreover, Grobys and Huhta-Halkola (2019, 2881) also noted returns from the employed value strategy to decrease after considering the size effect, implying that the value premium is partly but not fully driven by size effect in the Nordic stock market.

2.2 Explanations for returns from value and contrarian investment strategies

Several explanations have been suggested by academic literature to explain the value premium or returns from contrarian investment strategies. Chan (1988, 147) describes contrarian investment strategies as selling winners and buying losers. In the early days of fundamental investing, Graham and Dodd (1934) argued that the possible mispricing of stocks could originate from analysts extrapolating earnings growth too far into the future. In this sense, cheap stocks could falsely be thought to stay cheap by investors due to the extrapolation of past poor performance into the future. Furthermore, De Bondt and Thaler (1985, 793) investigated whether the overperformance of a value portfolio was a result of the stock market overreacting to unexpected and dramatic news events. The authors found the value portfolio to outperform the growth portfolio in NYSE in the 1926-1982 period, suggesting that the market is irrational and overreacts to information (De Bondt & Thaler 1985, 800-804). Both explanations violate the efficient market hypothesis, which in its strong form assumes the market price of stocks to reflect all available information efficiently implying that all stocks are always traded at their fair value and new information is priced in immediately after its release, thus the making of continuous superior returns should not be possible (Chen 2016, 13-14).

Fama and French (1996, 82) argued that the three-factor asset pricing model explains returns on portfolios formed on size and book-to-market value of equity thus any excess returns not explained by the model is simply risk not captured by the model. Furthermore, Chen and Zhang (1998, 534) argued that higher returns of value stocks are compensation for taking on more risk. In contrast, Zarowin (1990, 124) argued that evidence provided by De Bondt and Thaler (1985) was not a result of investor overreaction but size disparity between winners and losers, which could not be explained by differences in risk (beta) or the January effect. Moreover, Jegadeesh (1992, 349) found that returns related to size could not be explained by betas using test portfolios with small cross-sectional correlation between betas and size.

Gottesman, Jacoby and Li (2017, 11) argued that the returns of contrarian value portfolios could be based on compensation to investors for facing illiquidity. Furthermore, Balsara and Zheng (2005, 334, 341) found the contrarian investment strategy to work best with low-volatility or low trading volume stocks using a sample comprised of NYSE and AMEX listed stocks in the 1982-2004 period. The authors suggested that the returns of contrarian investment strategies could be a result of information assimilation offsetting information dissemination of low-volatility stocks, hence leading to an average speed of information diffusion and higher returns of low-volatility past losers compared to low-volatility past winners (Balsara and Zheng 2005, 342, 344).

2.3 Momentum investing

On the grounds of previous research (examples are presented below), a price momentum has existed and has been documented in the market and it presents evidence of the mispricing of stocks thus challenging the efficient market hypothesis. Momentum investing in general is described by Bird and Whitaker (2003, 223) as investing on the basis of past trends and price momentum as investing on the basis of past returns. Investors following a momentum investing strategy buy past winners and sell past losers relying on past trends to continue, which is opposite to a contrarian investing strategy, where investors sell past winners and buy past losers. Following the work of De Bond and Thaler (1985) momentum investing got more attention in the academic world after Jegadeesh and Titman (1993, 68) argued that "*if stock prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist*".

Jegadeesh and Titman (1993, 67, 89) further investigated the market overreaction hypothesis argued by De bond and Thaler (1985) and found trading strategies, which bought winners and sold losers over 3- to 12-month horizons, to yield abnormal returns in the 1965-1989 period using data from NYSE and AMEX. Later, Jegadeesh and Titman (2001, 702-703) re-examined the effectiveness of the trading strategy using improved data comprised of stocks from AMEX, NYSE, and Nasdaq in the 1990-1998 period. The authors addressed critique presented towards their previously utilized sample data by excluding all stocks priced below $5 at the beginning of each

holding period and all stocks falling in the smallest market capitalization stocks NYSE decile to remove the possibility of results being driven by small and illiquid stocks or a bid-ask bounce (Jegadeesh & Titman 2001, 702-703). Furthermore, consistent with the result presented by Jegadeesh and Titman (1993), the authors found momentum strategies to outperform in the first 12 months following the portfolio formation (Jegadeesh & Titman 2001, 701).

In addition, Chan et al. (1996, 1687-1688) found winners to outperform losers using a sample composed of NYSE, AMEX, and Nasdaq in the 1977-1993 period. The authors found past price performance to be closely aligned with past earnings performance (Chan et al. 1996, 1689). However, price momentum and the markets underreaction to earnings news were not the same phenomenon according to the authors, but instead they exploit underreaction to different pieces of information (Chan et al. 1996, 1697). Chan et al. (1996, 1710) argued that a stock with low past returns will on average experience low subsequent returns in a 3- to 12-month horizon, which supports the theory of the market underreacting to information.

Momentum investing strategies have also been reported to work in various other stock markets in addition to the U.S. stock market. Bird and Whitetaker (2003, 225, 237) constructed portfolios ranking stocks based on 6-month and 12-month prior returns to yield excess returns in the major European stock markets in the 1990-2002 period. Similarly, Fama and French (2012, 459, 471) reported strong momentum returns in North America, Europe and Asia Pacific regions excluding Japan in the 1989-2011 sample period. Furthermore, Bornholt, Dou and Malin (2015, 275, 301) employed a momentum strategy enhanced with trading volume used to predict momentum returns in 37 countries between 1995 to 2009, and found the volume-based momentum strategy to outperform a pure momentum strategy in 34 out of 37 countries thus presenting evidence of the predictive power of trading volume in identifying persistent momentum returns.

2.4 Explanations for momentum returns

Momentum investing strategies have continued to yield excess returns even after it has been recognized and well-documented as a stock market anomaly. However, it is

still unclear what explains the excess returns stemming from momentum investment strategies. For example, Balsara and Zheng (2005, 341) investigated whether stock volatility influences momentum returns, and reported a momentum strategy of buying past winners and short-selling past losers to yield the highest positive returns when employed in high-volatility stocks using six, nine- and twelve-month holding periods. Balsara and Zheng (2005, 343) suggested that the momentum strategy returns of high-volatility stocks may stem from the slow speed of information diffusion induced by the widespread information dissemination having an adverse effect on information assimilation. Therefore, regardless of information disseminating quickly, the low rate of information assimilation offsets the high rate of information dissemination slowing the speed of information diffusion resulting in high-volume stocks generating momentum profits (Balsara & Zheng 2005, 343).

In contrast, Campbell, Grossman and Wang (1993, 935) found evidence of daily momentum returns being lower on high-volume days than on low-volume days. Corroborative findings are also made by Conrad, Hameed and Niden (1994, 1328), who found high-volume stocks to experience price reversals or negative momentum returns and low-volume stocks to experience positive momentum returns. Lee and Swaminathan (2000, 2065) also studied trading volume in the prediction of cross-sectional stock returns and found high (low) volume stocks to earn lower (higher) returns using a sample of stocks listed in NYSE and AMEX in the 1965-1995 period. Moreover, Lee and Swaminathan (2000, 2065-2066) argued information diffusion to work on high-volume stocks and only low-volume stock returns to benefit from increase in volume. However, the authors did not find trading volume to be highly correlated with firm size or relative bid-ask spread implying that trading volume is not a proxy of firm size or bid-ask spread but a separate phenomenon from the two (Lee & Swaminathan 2000).

Furthermore, Lee and Swaminathan (2000) argued trading volume to possibly offer a link between intermediate-horizon momentum and long-horizon price reversal thus suggesting that trading volume may be used in identifying stock momentum cycle phases and possible price reversals. Lee and Swaminathan (2000) proposed that the market is in constant convergence toward intrinsic value hence both intermediate-horizon overreaction and long-horizon overreactions are observable phenomena of

prices reacting and settling to new information, which support the findings related to market overreacting to information presented by De Bondt and Thaler (1985). Moreover, Lee and Swaminathan (2000) note this suggestion to be consistent with the behavioural models of Barberis et. al (1999), Daniel et al. (1998) and Hong and Stein (1999), which are elaborated in the next chapter.

2.5 Behavioural models and momentum

A handful of behavioural models have been utilized to explain returns from momentum and contrarian investment strategies. Prior literature has proposed different explanations for stock price reversals and short- to medium-term and long-term returns, which are captured by momentum and contrarian investment strategies. Jegadeesh and Titman (2001, 718-719) found evidence supporting the behavioural explanations provided by Barberis, Shleifer and Vishny (1998); Daniel, Hirshleifer and Subrahmanyam (1998); and Hong and Stein (1999), but concluded that the results should be tempered with caution, since the behavioural models seem to only partially explain momentum returns due to not explaining the inconsistent occurrence of long-term return-reversals. The behavioural models are further discussed below.

2.5.1 Investor sentiment

Barberis et al. (1998, 308) investigated investor sentiment to understand how investor beliefs might lead to under- and overreactions in the stock market. To empirically study the possible behavioural explanations behind market under- and overreaction, Barberis et al. (1998, 308-309) created a model that combined heuristic representativeness introduced by Tversky and Kahneman (1974) and conservatism introduced by Edwards (1968). Heuristic representativeness is a theory of human behaviour to view events as representative of some class and to ignore the laws of probability in the process. According to Tversky and Kahneman (1974), the phenomenon of people recognizing patterns in truly random sequences is a manifestation of heuristic representation, which Barberis et al. (1998, 316) argued to be a suggestive example of the market overreaction. Furthermore, Conservatism theorises that the slow change in individual beliefs result in the slow updating of

models after gaining access to new information, which Barberis et al. (1998, 315) implied to be suggestive of market underreaction.

The model predicted stock prices to underreact to earnings announcements and similar events, by assuming that as information they are of low strength and have significant statistical weight (Barberis et al. 1998, 332-333). Furthermore, the model by Barberis et al. (1998) yielded a prediction that stock prices overreact to consistent patterns of good or bad news assuming consistent patterns of news represent information of high strength and low statistical weight.

Barberis et al. (1998) argued the strength and weight of different pieces of evidence employed in the model to be based on empirically supportable assumptions, which allowed valid derivation of empirical implications from the models. Moreover, Barberis et al. (1998) argued that priori classification of news events could allow the model to be used to test a theory proposed by Griffin and Tversky (1992), which argued people to accentuate the effect of strength of news and underrate the statistical weight of news. In the context of the paper of Barberis et al. (1998), the theory predicts that holding the weight of news constant, one-time strong news events should cause an overreaction in the market.

2.5.2 Investor overconfidence

Daniel et al. (1998, 1841, 1865) developed a theory based on investor overconfidence, and variations in confidence arising from self-attribution bias related to investment outcomes. The former aspect of the theory suggests that people are generally overconfident of their abilities and the latter suggests that an investor's confidence grows when public information is in line with the prior information of the investor, but does not fall respectively when public information contradicts this prior information (Daniel et al. 1998, 1844). The theory proposes that investors overreact to private information signals and underreact to public information events (Daniel et al. 1998, 1865).

Daniel et al. (1998, 1865) reported that positive return autocorrelation (used in correspondence with underreaction to new information) can be a result of continuing

overreaction, which can be subsequently followed by long-run correction, thus allowing the short-run positive autocorrelations to be consistent with long-run negative autocorrelation (used in correspondence with overreaction to new information) in its initial phase. In other words, momentum returns can arise from the result of continuing overreaction in the initial phase of repeated arrival of public information, which gradually draws the price back towards fundamentals resulting in negative momentum returns in the long run (Daniel et al. 1998, 1856). Therefore, the initial overreaction phase can be consistent with short-run autocorrelation (momentum returns), which later leads to a return reversal in the long-term, when the overreaction reaches its terminal phase (Daniel et al. 1998, 1865).

Furthermore, the theory developed by Daniel et al. (1998) explains long-run abnormal returns following average public event stock price reactions of the same sign, also referred to as market underreaction, and elaborates whether price movements around public events can be predicted. Based on the theory, Daniel et al. (1998) argued that underreaction to new public information is neither a necessary nor a sufficient condition for predicting stock price changes related to news events. Instead, underreaction can cause predictability only if an event is chosen in response to market mispricing. Alternatively, Daniel et al. (1998) argued that stock price predictability can arise when a public event induces a continuing overreaction. Since the model is based on overconfidence of investors who possess private information, Daniel et al. (1998, 1867) argued the return predictability to be the strongest in companies with the greatest information asymmetries, which also proposes that small companies with assumedly greater information asymmetries have greater inefficiencies in stock prices.

2.5.3 Boundedly rational agents

Hong and Stein (1999, 2144) investigated the behavioural differences between two types of agents assumed boundedly rational: news watchers and momentum traders. The news watchers make forecasts about future fundamentals based on signals they observe and do not establish their forecasts on current or past prices (information is not extracted from stock prices), whereas momentum traders establish their opinions and decisions on past price changes (Hong & Stein 1999, 2144-2145). The model only

incorporates gradually diffusing news about fundamentals thus excluding exogenous shocks to investor sentiment and liquidity motivated trades (Hong & Stein 1999, 2146). The results of the model revealed that the short run underreaction induced by news traders eventually leads to overreaction in the long run, after momentum traders employ simple arbitrage strategies (Hong & Stein 1999, 2169).

2.6 Long-term reversal effect and risk of momentum crash

Already De Bondt and Thaler (1985) documented long-term return reversals investigating returns from buying losers and selling winners. Similarly, Jegadeesh and Titman (1993, 89) found half of the gained medium-term 3- to 12-months momentum returns to disseminate within the following two years after the portfolio formation date. Daniel and Moskowitz (2016, 242) found momentum strategies shorting loser stocks in bear market states to face a crash from loser stocks experiencing strong gains when the market starts to rebound; the phenomenon is referred to as momentum crash. Furthermore, Barroso and Santa-Clara (2016, 112, 119) also found the risk for a momentum crash to be a potential downside for momentum strategies, but claimed that crashes could be avoided by employing daily return variance in predicting crashes increasing the Sharpe ratios of momentum strategies.

2.7 CAPM and beta

The capital asset pricing model referred to with the acronym CAPM developed by Sharpe (1964) and Lintner (1965) is based on the mean-variance framework composed by Markowitz (1952), where investors are assumed to be risk-averse thus maximizing expected return and minimizing variance of investment portfolios. The CAPM relies on theoretical market equilibrium derived from hypothetical assumptions. Sharpe (1964) and Lintner (1965) extended the Markowitz mean-variance model by adding two important assumptions: all investors can borrow or lend with a common pure rate of interest or risk-free rate, and investor expectations are homogenous implying that all investors view investment opportunities similarly in terms of expected return and risk. Lintner (1965) further elaborates the market equilibrium by assuming that stocks are traded in a single purely competitive market, where transaction costs

and taxes are non-existent. The relationship between the market risk and return of an asset predicted by CAPM can expressed with the following formula:

$$E(R_i) = R_f + \beta_{im}[E(R_m) - R_f]$$

(1), where

$E(R_i) = expected\ return\ of\ an\ asset$

$E(R_m) = expected\ return\ of\ the\ market$

$R_f = risk - free\ rate\ of\ return$

$\beta_{im} = the\ market\ beta\ of\ an\ asset.$

The beta coefficient between the investment and the market, also known as the market beta, is described by Black (1972, 444) as the slope of the regression line relating the return of an asset and the return of the market. Fama and French (2004, 28) describe an interpretation of beta as sensitivity to the variance of the market return. In other words, the market beta measures market risk or systematic risk of a portfolio, which cannot be mitigated through diversification. The market portfolio always has a beta of one. Furthermore, a beta value larger (smaller) than one means the return of an asset varies more (less) compared to the return of the market. Black (1972) reports the definition of beta as dividing the covariance of the return of an asset with the return of the market portfolio by the variance of the market return:

$$\beta = \frac{cov(r_i, r_m)}{\sigma_m^2}$$

(2), where

$cov(r_i, r_m) = the\ covariance\ between\ the\ return\ of\ an\ asset\ with\ the\ market\ return$

$\sigma_m^2 = the\ variance\ of\ the\ market\ return.$

The CAPM and the ability of market beta to predict future stock returns has been widely criticized by academic practitioners. For example, Fama and French (1992, 449) found the simple relation between market beta and average return to disappear in NYSE stock returns between 1963-1990. The authors also reported the relation to be weak in 1941-1990 period. Furthermore, the inability of the CAPM to explain returns stemming for example from firm size (see for example Banz 1981; Fama & French

2015), earnings-to-price and book value-to-market value of equity valuation multiples (see for example Basu 1983, Fama & French 1992, 2006, 2015), and momentum (see for example Jegadeesh & Titman 1993), more complex asset pricing models have been introduced (see for example Carhart 1997; Barillas & Shanken 2018; Daniel, Hirshleifer & Sun 2017; Fama & French 1992, 2015, 2018; Hou, Xue & Zhang 2015; Hou, Mo, Chen & Zhang 2018, 2019) to extend the CAPM. These extended asset pricing models are commonly referred to as factor models.

3. DATA AND METHDOLOGY

The data consists of the financial statement information of stocks listed in Nasdaq Helsinki and Finnish 10-year government bond yield data, which are collected from Thomson Reuters Eikon database (date of retrieval 09-06-2020) and supplemented with data from Thomson Reuters DataStream database (date of retrieval 06-07-2020). The 10-year average of the Finnish government bond yield illustrated in (Figure 1) is employed as the risk-free rate for the entire investigated period, which has a value of 1.24 percent.

Figure 1: 10-year Finnish government obligation yield

The portfolios used in the study are composed of non-financial stocks quoted in Nasdaq Helsinki during May 2010 to May 2020 period. Financial companies are

excluded since it is considered a good practise in finance literature adopted from (Fama & French 1992, 429), who argued that the high level of leverage of financial companies does not have the same meaning for non-financial companies, because high leverage more likely indicates distress in non-financial companies. Furthermore, double-listed stocks are excluded and in case of a stock having more than one stock series listed, the series with the highest liquidity is included in the sample. The number of stocks in the beginning of each holding period varies from 104 to 111 stocks depending on the year of portfolio formation.

The portfolios are equally weighted at the start of each holding period and changes in portfolio weights are included in the calculation of monthly returns during each 1-year holding period. To account for the survivor bias, if a stock is delisted in the sample period, it will be sold at the closing price of its last trading day. Survivor bias in the context of finance originates from mutual fund research, in which the bias refers to the overstatement of mutual fund performance as a result of investigating only the performance of funds that have not ceased to exist leaving the closed or merged funds out of the utilized sample (Elton, Gruber & Blake 1996, 1097-1098). In this case, the inclusion of dead or delisted companies in the sample considers the survivor bias in the results derived from the sample.

If a stock has gone bankrupt during the 2010-2020 period, the return on it will be minus 100%. In addition, received dividends are reinvested into the stocks that distributed the dividends to avoid any biases originating from different dividend yields of stocks included in the portfolios. This is achieved by utilizing total return values, which considers all dividends received thus allowing the inclusion of dividends in the calculations of portfolio returns.

3.1 Portfolio formation

To investigate the effectiveness of EBIT/EV and 3-month momentum in stock picking, value-winner P1 and growth-loser P2 portfolios are composed. To answer the second research question, four more portfolios are constructed: Momentum-winner P3, Momentum-loser P4, Pure-value P5 and Pure-growth P6. In addition, a market portfolio is calculated from the sample to allow the comparison of the returns of all

investment strategies to the return of the market, which usually serves as a benchmark for investors.

The portfolios are composed using ranking, which allows the creation of TOP and BOTTOM quintile portfolios that represent counterpart portfolios in comparison to each other; the TOP and BOTTOM portfolio pairs are P1 & P2, P3 & P4, and P5 & P6. Moreover, the TOP and BOTTOM quintile portfolios are formed by taking the top 20% and bottom 20% of stocks based on the ranking scores. Since, the focus of this study is to determine the effectiveness of the value-winner strategy P1 and investigate whether the combination portfolio outperforms the traditional pureplay strategies, the pureplay investment strategies are created to complement the analyzation of the performance of the combination portfolios P1 and P2. A more in dept description of the formation of portfolios P1-P6 is provided below.

The formation of the combination portfolios P1 and P2 is executed by utilizing average ranking. The findings of Grobys and Huhta-Halkola (2019, 2876, 2882) support the utilization of average ranking in this study, since the authors found the average ranking scheme to offer the best performance compared to methods selecting value and momentum stocks by employing a 50/50 split or double-screening value and momentum stocks. Therefore, the stocks in the sample are ranked based on EBIT/EV valuation multiple and then based on total returns similarly to the method described by Grobys and Huhta-Halkola (2019, 2079-2880). The employed enterprise and EBIT values at every rebalancing date are derived from company specific latest fiscal year financial statements.

First, stocks are ranked in descending order based on EBIT/EV values, where the rank value of one corresponds to the highest multiple value. Subsequently, stocks are ranked in descending order based on the employed momentum factor, past 3-month return, where the rank value of one corresponds to the highest past 3-month return of a stock before the portfolio formation date. Second, stocks with negative EBIT/EV values are excluded before portfolio formation to avoid vague or ambiguous results. Then, an average rank is calculated for each stock by calculating the average from the two described rankings. As a result, the high rank P1 and low rank P2 portfolios are created.

The pure momentum portfolios P3 and P4 are composed by ranking stocks based on their past 3-month return prior to portfolio formation, where P3 represents the high-ranking portfolio and P4 the low-ranking portfolio, respectively. Similarly, the pureplay portfolios P5 and P6 are composed by ranking stocks based on EBIT/EV values at the time of portfolio formation. All portfolios, excluding the market portfolio, are reformed on every rebalancing date, which is the first trading day of May, at a 1-year frequency. The portfolios are composed in May to consider the look-ahead bias originating from different release times of stock information due to differences in company specific fiscal periods.

3.2 EBIT/EV

The use of inverse EV/EBIT multiple allows the inclusion of stocks with an EBIT of zero when screening stocks since the denominator is replaced with enterprise value. Moreover, the inverse multiple allows better interpretation of stocks with a falsely high EV/EBIT value stemming from the value of EBIT being close to zero. In addition, the use of enterprise value captures the effects of leverage thus enabling better comparison between stocks with different levels of debt. Furthermore, the use of enterprise value instead of stock price alone, for example, removes the possibility of a stock boosting its EBIT figure with debt, and therefore signalling better than actual performance. This is an issue with price-to-earnings multiple, for example. Moreover, depreciations and amortizations are included the calculation of measuring profitability using EBIT and they are considered to a cost for a company. The general formula for calculating EBIT/EV multiple is:

$$\frac{EBIT}{EV} = \frac{Earnings\ before\ interest\ and\ taxes}{Market\ capitalization + Total\ debt - Cash\ and\ cash\ equivalents} \tag{3}$$

However, it is worth noting that the EBIT values collected from the databases exclude non-operating income and expense from the calculation of EBIT. Even though EBIT/EV multiple covers more dimensions of company valuation compared to price-

to-earnings, for example, it may not capture all aspects of stock valuation. EBIT may also prefer companies that operate with less depreciation and amortization costs. However, since there is very little literature about the use of EBIT/EV multiple in portfolio formation, only very subjective arguments can be made by the author of the use of EBIT/EV multiple in portfolio formation.

3.3 Performance evaluation

The performance evaluation is based on monthly total return time-series data. Performance measures utilized in the study are raw average return and three risk-adjusted return measures: the Sharpe ratio, the modified Sharpe ratio, and the single factor alpha, also known as the Jensen alpha. From the risk-adjusted measures, the Sharpe ratio considers the total risk of the employed portfolios, the modified Sharpe ratio employs modified value-at-risk to measure risk, and the Jensen alpha measures systematic risk by utilizing beta. The total risk of an investment consists of systematic risk and idiosyncratic risk. Systematic risk or market risk refers to undiversifiable risk and idiosyncratic risk or non-market risk refers to diversifiable risk (Sharpe 1995). Due to the potential of underlying idiosyncratic risk left in the employed portfolios, risk-adjusted measures based on total risk may be considered more reliable, when evaluating performance of portfolios employed in this study. However, the Jensen alpha is employed in addition, since it may provide useful insight on the relative performance of the employed portfolios compared to the market portfolio.

3.3.1 The Sharpe Ratio

The calculation of the Sharpe ratio is based on the reward-to-variability framework introduced by Sharpe (1966). The ratio measures excess return relative to standard deviation of the investment originally introduced in the risk-return framework by Markowitz (1952) as a proxy for risk. A high Sharpe ratio indicates a high risk-adjusted return, and vice versa. Furthermore, the ratio may help investors to identify, whether higher portfolio returns are a result of taking on more risk or caused by implementing an investment strategy successfully, when comparing the ratio to a benchmark. The Sharpe ratio is calculated by subtracting the risk-free rate from the rate of return of the portfolio and dividing the result by the standard deviation of the portfolio returns:

$$Sharpe\ Ratio = \frac{R_i - R_f}{\sigma_i}$$

(4), where

$R_i =$ the average monthly return of portfolio i

$R_f =$ the employed risk − free rate

$\sigma_i =$ the average monthly standard deviation of portfolio i.

The Sharpe ratio has been criticized as a performance measure since it does not consider the effects of possible return distribution asymmetries and fat tails (skewness), which may lead to underestimation of risk and overestimation of performance (Eling & Schuhmacher 2007, 2633-2634). The danger of return distribution asymmetries jeopardizing validity may be a problem with momentum returns, since momentum reports have been reported to have skewed return distributions. For example, Gregory-Allen, Lu and Stork (2012, 296) observed momentum-winner (-loser) strategies to have wide (narrow) left and narrow (wide) right tails. The momentum portfolios employed by Gregory-Allen et al. (2012) were composed identically to Jegadeesh and Titman (2001) and used data from NYSE, AMEX, and NASDAQ from 1926-2009. In addition, standard deviation does not differentiate between positive and negative changes from the mean, which may affect the validity of standard deviation as a risk surrogate.

3.3.2 The modified Sharpe Ratio

To consider the possibility of skewness and kurtosis in portfolio return distributions, the modified Sharpe ratio developed by Favre and Galeano (2002) is employed, where modified Value-at-Risk (mVaR) is utilized as a measure for risk. Value-at-Risk measures the amount of maximum loss from an investment in a chosen period with a probability of 1- α, where α denotes the significance level determining the confidence interval (Eling & Schuhmacher 2007, 2636; Favre & Galeano 2002). A loss probablity alpha of 10% is used in the mVaR calculations in this study resulting in a 90% risk level. The equation of the modified Sharpe Ratio is presented below followed with a short explanation on calculating the modified Value-at-Risk.

$$Modified\ Sharpe\ Ratio = \frac{R_i - R_f}{mVaR}$$

(5), where

$R_i =$ the average monthly return of portfolio i

$R_f =$ the risk − free rate

$mVaR =$ the modified Value − at − Risk.

Arzac and Bawa (1977) proposed Value-at-Risk to be equal to standard deviation as a risk surrogate if returns are normally distributed. Therefore, any skewness or excess kurtosis of a return distribution should be considered, when employing the Value-at-Risk as a risk surrogate in investing. The framework of Favre and Galeano (2002) is applied to consider the possible skewness and kurtosis of return distributions, a second order Cornish-Fisher (1937) expansion is employed to calculate an adjusted Z value:

$$Z_{CF} = Z_C + \frac{1}{6}(Z_C^1 - 1)S + \frac{1}{24}(Z_C^3 - 3Z_c)K - \frac{1}{36}(2Z_C^3 - 5Z_C)S^2$$

(6), where

$Z_C =$ critical value for probability $(1 - \alpha)$

$S =$ skewness of the return distribution

$K =$ kurtosis of the return distribution.

In addition, the parameter μ is added to the equation as suggested by Wilmott (1998) to consider the drift of the asset value stemming from longer term horizons inducing right skewed return distributions. After these adjustments, the equation of mVaR proposed by Favre and Galeano (2002) can be written as:

$$mVaR = W(\mu - Z_{CF}\sigma)$$

(7), where

$Z_{CF} =$ critical value for probability after the Cornish − Fisher expansion $(1 - \alpha)$

$W =$ amount at risk or portfolio

$\sigma =$ yearly standard deviation

$\mu = the$ rate of the drift of portfolio value.

3.3.3 Jensen alpha

The Jensen alpha measures the excess return over the return predicted by the CAPM, which utilizes regression intercept to measure alpha with the slope of the regression line corresponding to the beta of the asset (Jensen 1968). The alpha of the benchmark index is always zero and alpha values larger (smaller) than zero imply that an asset overperforms (underperforms) the benchmark index, which in this case is the market portfolio. The Jensen alpha is employed to calculate ex post alphas with linear regression. Furthermore, the single factor adjusted R-square represents the proportion of portfolio returns explained by the market. The proportion of returns not explained by the market is considered as idiosyncratic risk left in left in the portfolio or risk not explained by the CAPM. The formula for calculating the Jensen alpha is the following:

$$\alpha = R_i - R_f - \beta_i(R_m - R_f)$$

(8), where

$\alpha = the\ Jensen\ alpha\ of\ portfolio\ i$

$R_i = the\ return\ of\ portfolio\ i$

$R_f = the\ risk - free\ rate$

$\beta = the\ beta\ coefficient\ of\ portfolio\ i.$

3.4 Significance testing

To check the validity of the results, statistical significance testing on the performance measures is conducted. Two previous versions recognized by the academic finance literature on testing the statistical significance of the Sharpe ratio are the Jobson and Korkie (1981) test and alternatively its corrected version by Memmel (2003). However, Ledoit and Wolf (2008, 850, 858) argued that the tests are not valid when return distributions have heavier tails or when time series data is utilized. Furthermore, a studentized time series bootstrap is recommended by Ledoit and Wolf (2008) for small to moderate sample sizes over two alternative inference methods relying on asymptotic normality by Andrews (1991), and Andrews and Monahan (1992). The two alternative methods are robust with larger samples, but the methods often tend to

return a type one statistical error by rejecting a true null hypothesis when employed on small sample sizes (Ledoit & Wof 2008, 853).

Thus, to consider the effect from potentially skewed returns, a studentized circular block bootstrap method proposed by Ledoit and Wolf (2008) is employed to test the significance of the Sharpe ratios, which applies circular block bootstrap of Politis and Romano (1992). This may prove to be particularly useful in testing Sharpe ratios of portfolios employing a momentum strategy partially or fully, since momentum may cause skewness in return distributions (see for example, Gregory-Allen et al. 2012). Consequently, a circular bootstrap developed by Ardia and Boudt (2015) is employed to test the significance of modified Sharpe ratios, which also utilizes the circular block bootstrap methodology of Politis and Romano (1992).

The statistical significances of the Sharpe ratio and the modified Sharpe ratio are tested using an R package called: "*PeerPerformance*" by Ardia and Boudt (2020), which utilizes the methodology described in Ledoit and Wolf (2008), and Ardia and Boudt (2015). An example of utilizing the open source statistical package is documented by the developers of the package in Ardia and Boudt (2018). The number of bootstrap replications for computing the p-value is kept at default 499 replications and the block length in the circular bootstrap is set to use the optimal block-length determined by the R package function.

The significance of the Jensen alpha values is tested with Welch t-test utilising Newey-west (1994) standard errors to consider the possible effects of heteroskedasticity and autocorrelation stemming from the use of time series data. Furthermore, the normality of the regression residuals is tested with the normality test of Jarque and Bera (1980). The normality of the portfolio excess returns of all portfolios is tested statistically with Shapiro-Wilk test, and the single factor alpha regression is tested for heteroskedasticity with Breusch-Pagan test. In addition, exploratory data-analysis is conducted on all portfolio excess returns and regression residuals with R programming language. The R script written by the author of this study is presented in appendix 9 for further information on all statistical testing and data-analysis.

4. RESULTS

The results of each investment strategy are reported from the hypothetical viewpoint of an investor. Based on the employed performance metrics, the winning investment strategy is identified from the set of investigated investment strategies from the 10-year sample period. The return, risk and performance metrics of the investigated portfolios are reported in table 1. First, the cumulative returns of each investment strategy are shortly elaborated. Second, the average annualized return and volatility are discussed together with the employed risk-adjusted performance measures and their statistical significances. In addition, potentially insignificant results are observed and reported. Finally, the validity of the results is evaluated by observing distributional implications of the excess returns, and the single factor alpha regression residuals are investigated for normality and potential heteroskedasticity. The validity and analysis of return distributions are discussed in the following chapter.

In the end of the 10-year period, the value-winner P1 portfolio would have cumulated significantly more return compared to all the investigated portfolios and the market. Furthermore, the pure-value P5 portfolio would have cumulated the second largest amount of cumulative return and momentum-winner P3 portfolio the third largest amount. In contrast, the momentum-loser portfolio P4 would have yielded the lowest cumulative return, and both value-loser P2 and pure-growth P6 portfolios in addition to the momentum-loser P4 portfolio would have underperformed compared to the market in terms of cumulative return. It is important to examine the relationship between portfolio return and the chosen risk metric to reveal whether higher portfolio return is simply a result of accepting higher risk or implementing a superior investment strategy.

The value-winner portfolio P1 would have outperformed all investigated portfolios and the market on all employed risk-adjusted measures. The value-winner strategy would have yielded a 0.503 points larger Sharpe ratio compared to the market with a p-value of ~0.008 and a 0.642 points larger modified Sharpe ratio with a p-value of ~0.002, respectively.

Table 1: Return, risk and performance metrics of the investigated portfolios (May 2010 - May 2020)

Portfolio	*Cumulative return*	*Average annual return (%)*	*Average annual volatility (%)*	*mVaR*	*SR vs Market*	*Sign.*	*MSR vs Market*	*Sign.*	*Alpha*	*Sign.*	*Market beta*	*Adj. R^2*
P1	364.75	16.90	16.88	0.005	0.503	(0.008)	0.642	(0.002)	0.091	(0.000)	0.93***	0.855
P2	93.68	8.09	17.05	-0.049	-0.020	(0.864)	-0.013	(0.882)	0.001	(0.953)	0.95***	0.877
P3	181.93	12.20	18.81	-0.013	0.160	(0.178)	0.180	(0.228)	0.036	(0.086)	1.03***	0.860
P4	-14.12	0.58	20.46	1.542	-0.452	(0.002)	-0.442	(0.002)	-0.084	(0.005)	1.09***	0.810
P5	249.62	14.12	17.43	-0.003	0.316	(0.002)	0.344	(0.006)	0.06	(0.001)	0.97***	0.881
P6	68.43	6.88	18.05	-0.081	-0.109	(0.316)	-0.128	(0.264)	-0.015	(0.443)	1.01***	0.889
Market	99.35	8.36	16.87	-0.046								[1]

Notes: The annualized average returns, risk measures (volatility and mVaR) of the corresponding risk metrics Sharpe ratio (SR) and the modified Sharpe ratio (MSR) are presented for all investigated portfolios and the market portfolio. The SR values and the MSR values have been converted to annualized ratios by multiplying the monthly ratios by $\sqrt{12}$. The presented SR and MSR values indicate the performance difference between each portfolio and the market portfolio. Next to the SR and MSR values, the significance levels are reported in parenthesis. The significances of the SR values are tested by Ledoit-Wolf test statistics and the MSR values are tested by Ardia-Boudt test statistics, respectively. In addition, the Jensen alpha and market beta values are presented with the significance of the alphas tested by Welch t-test using Newey-West standard errors. The reported alphas have been annualized by multiplying the monthly alpha values by 12. Statistical significances of the reported market beta values are reported as follows: *** is significant at 1 % level, ** is significant at 5 % level and * is significant at 10 % level.

[1] The R package PeerPerformance from Ardia and Boudt (2020) is utilized in the calculations of SR, MSR, and the significance SR and MSR significance tests. More information on the R package can be found from: https://CRAN.R-project.org/package=PeerPerformance

The value-winner strategy would have yielded over twice fold the annualized average return (~16.90%) over the market portfolio (~8.36%) with the approximately the same amount of annualized volatility (~16.88%) compared to the market (~16.87%), which may explain the clear overperformance of the value-winner strategy using the Sharpe ratio as a performance measure. Furthermore, the mVaR value of the value-winner portfolio would have been approximately 0.005.

The strategy would have generated ~0.091 of alpha over the expected return predicted by the CAPM with a p-value of smaller than 0.000 indicating that the strategy would have outperformed the market portfolio in terms of ex post returns. Furthermore, the value-winner portfolio would have had the smallest market beta of 0.93*** compared to all the investigated investment strategies implying that it would have been the least risky investment strategy compared to both the market and the group of investigated investment strategies in terms of employing beta as a measure of risk. However, considering the flaws of the CAPM and its inability to perfectly capture stock market returns, the value-winner P1 portfolio's adjusted R-Square value of 0.855 suggests that the traditional CAPM explains ~85.5% of the returns of portfolio P1. Thus, the amount of idiosyncratic risk left in the portfolio would have been ~14.46% based on the adjusted R-square value.

The second-best investment strategy in the investigated 10-year period would have been the pure-value strategy. The ex post annualized average return for the pure-value investment strategy would have been approximately 14.12%, the annualized average volatility ~17.43%, and mVaR negative 0.003. The Sharpe ratio would have been 0.316 points larger compared to the market with a p-value of ~0.002, and the modified Sharpe ratio 0.344 with a p-value of ~0.006, respectively. The pure-value strategy would have generated ~0.06 of alpha over the expected return predicted by the CAPM with a p-value of ~0.001. The ex post market beta of the portfolio P5 of 0.97*** is the third smallest from the investigated portfolios, and it implies that the portfolio is less sensitive to market fluctuation of asset value; the portfolio is less risky compared to the market in terms of beta. Moreover, the amount of idiosyncratic risk left in the P5 portfolio would have been ~11.93% based on the adjusted R-square value of 0.881.

Subsequently, the third best investment strategy would have been the momentum-winner strategy, which would have yielded approximately 12.20% of annualized average return with an annualized average volatility of approximately 18.81%, and negative 0.013 value of mVaR. The momentum-winner strategy would have yielded 0.160 points larger Sharpe ratio and 0.180 points larger modified Sharpe ratio compared to the market with p-values of ~0.178 and ~0.228, respectively. The momentum-winner strategy would have generated ~0.036 of alpha over the expected return predicted by the CAPM with a p-value of ~0.086. Based on the p-values of all the risk-adjusted performance indicators of the portfolio P3, the results are not statistically significant, and are therefore not reliable. The market beta of P3 is 1.03*** suggesting that the momentum-winner strategy would have been riskier in terms of beta compared to the market. Furthermore, based on the CAPM, the R-square value of 0.860 suggests that the amount of idiosyncratic risk in the P3 portfolio is ~13.98%.

In contrast, the worst performing portfolio was the momentum-loser portfolio P4, which would have returned ~0.54% of annualized average return with an annualized average volatility of ~20.46%, and 1.542 value of mVaR. The momentum-loser portfolio would have returned 0.452 points less Sharpe with a p-value of ~0.002 and 0.442 less modified Sharpe ratio with a p-value of ~0.002 compared to the market portfolio. The strategy would have induced ~0.084 of negative alpha with a p-value of ~0.005, thus underperforming compared to the market. The momentum-loser would have had a market beta value of 1.09*** implying higher risk compared to the market. In addition, the adjusted R-square value of the portfolio P4 would have been 0.81, suggesting that the amount of idiosyncratic risk in the portfolio based on the single factor CAPM would have been ~18.98%. Based on all the employed risk-measures, the momentum-loser portfolio would have been the riskiest investment strategy, and thus most susceptible to loss in portfolio value.

The growth-loser portfolio P2 would have returned approximately 8.09% of annualized average return with an annualized average volatility of ~17.05%, and -0.049 mVaR. The strategy would have returned 0.02 points less Sharpe with a p-value of ~0.864 and 0.013 less modified Sharpe with a p-value of ~0.882 compared to the market. On the contrary, the strategy would have generated ~0.001 of positive alpha with a p-value of ~0.953. The market beta of the growth-loser strategy would have implied less

risk compared to the market with a value of 0.95***. The adjusted R-square value would have been 0.877 suggesting that the portfolio P2 would have had ~12.31% of idiosyncratic risk left in the portfolio. The p-values of all the risk-adjusted measures of P2 are not statistically significant. Therefore, it is impossible to reliably compare the performance of P2 to its counterpart portfolio P1.

The pure-growth strategy would have returned ~6.88% of annualized average return with an annualized average volatility of ~18.05%, and a negative mVaR value of 0.081. The strategy would have returned 0.109 less Sharpe and 0.128 less modified Sharpe compared to the market portfolio with p-values of ~0.316 and ~0.264, respectively. Furthermore, the strategy would have generated a negative single factor alpha of ~0.015 with a p-value of ~0.443 and a market beta of 1.01*** implying slightly more risk compared to the market using beta as risk measure. The adjusted R-square value of 0.889 implies that the CAPM would have explained almost 90% of the returns, while the amount of unexplained return or the idiosyncratic risk would have been ~11.08%.

4.1 Validity of the results

The boxplots reported in appendix 4 visualize the monthly excess return distributions of the investigated portfolios and supports the interpretation of the descriptive statistics table presented in appendix 1. All the portfolio excess returns have data-points considered outliers, which may influence the validity of the results due to affecting the values of mean and standard deviation of each portfolio, for example. Consequently, this may affect the risk measures utilizing standard deviation and modified Value-at-Risk as measures of risk. Furthermore, the boxplots and histograms reported in appendices 4 and 5 both illustrate the high kurtosis of all the portfolios, which may influence the validity of the results.

All the portfolios, except momentum-loser portfolio P4, are negatively skewed based on the descriptive statistics. Surprisingly, the momentum-loser portfolio P4 exhibits a small amount of positive skewness and the growth-loser portfolio P2 has significantly smaller amount of negative skewness in comparison to the pure-growth portfolio P6, which in line with the findings of Gregory-Allen et al. (2012). The amount of negative skewness of portfolios P1 and P3 may be caused by implementing fully or partially a

long-only momentum-winner strategy. However, the market portfolio is also negatively skewed, and the pure-value portfolio P5 has the largest amount of negative skewness, which could also explain why the value-momentum portfolio P1 has a large amount of negative skewness in comparison to the investigated portfolios. Therefore, it is difficult to assess whether the inclusion of momentum affects the skewness of the long-only portfolios utilizing momentum.

Based on the Shapiro and Wilk test results, the excess return distributions of all investigated portfolios do not follow normal distributions on 1% risk level, except the momentum-loser portfolio P4 (Appendix 1). In addition to statistically testing the normality of the return distributions, QQ-plots are also reported in appendix 6 to further visualize, whether the distributions differ from a normal distribution. The QQ-plots of all portfolios except portfolio P4 illustrate that the plotted dot values deviate from the straight line suggesting that the return distributions of portfolios P1-P3 and P4-P6 do not follow a normal distribution. The Sharpe ratio is more susceptible to return distribution asymmetries compared to the modified Sharpe ratio, because the modified Sharpe ratio employs the Cornish-Fisher expansion in the mVaR calculation, which considers the possible effects of return distribution asymmetries. Therefore, the modified Sharpe ratio is more reliable in measuring performance compared to the Sharpe ratio.

The single factor alpha residuals are not normally distributed based on the Jarque-Bera test results implying that the single factor alpha regressions are potentially non-reliable. The QQ-plots on regression residuals reported in appendix 8 also reveal minor deviations from a normal distribution. Furthermore, residual plots are reported in appendix 7 to investigate, whether the regression results are affected by heteroskedasticity of the residuals. Based on the residual plots, there seems to be no detectable heteroskedasticity. However, the Breusch-Pagan test results reported in appendix 2 suggest that the pure-growth portfolio P6 suffers from heteroskedasticity, if assuming risk levels of 1% or 5%. This suggests that the alpha of portfolio P6 could be affected by potential heteroskedasticity. However, the Newey-West standard errors should consider the effects of heteroskedasticity in the results.

A correlation matrix reported in appendix 3 illustrates Pearson's correlation between all the portfolios and the market. All investments are strongly correlated with each other and especially with the market. Based on the correlation matrix, all the portfolios of the sample may be highly dependent on the movements of the market portfolio in general. This is also supported by the market beta values close to the market beta of the market portfolio, which always has a value of one. The strong correlations between portfolios may explain why the amount of idiosyncratic risk between the investigated portfolios are relatively close to each other.

Furthermore, the small sample size, highly limited stock universe and the exclusion of financial firms from the sample may greatly influence the possibility to generalize from the results of this study. It may provide context bound information about the use of EBIT/EV valuation multiple and 3-month momentum in stock picking. Since, the use of EBIT/EV is not extensively studied in finance literature to the best of my knowledge or the combination of EBIT/EV and momentum, the cross checking of results to improve validity is difficult. However, some interesting similarities can be observed that are in line with prior academic studies that have investigated value-momentum combination portfolios in different markets. The similarities are discussed in the last chapter below.

5. SUMMARY AND CONCLUDING REMARKS

To answer the first research question, the value-winner strategy employing a momentum enhanced EBIT/EV portfolio would have been the most profitable investment strategy based on raw average return and all chosen risk-adjusted measures. The value-winner portfolios ex post Sharpe and modified Sharpe are significantly larger compared to the market with an average annual volatility very close to the volatility of the market. Furthermore, the strategy would have generated ~0.091 points of alpha with the smallest market beta compared to all investigated portfolios. However, the value of ex post alpha is not exceptionally large. The performance metrics of the value-winner portfolio P1 are statistically significant. Furthermore, the value-winner strategy's outperformance over the momentum-winner and pure-value strategies suggests that the enhancement of a value strategy employing EBIT/EV valuation multiple with momentum, and vice versa, increases risk-adjusted returns.

The superior performance of the value-winner strategy portfolios is in line with prior research investigating the performance of value portfolios enhanced with momentum in various European stock markets (see for example Bird & Whitaker 2004; Grobys & Huhta-Halkola 2019; Leivo & Pätäri 2011).

In contrast, the worst performing investment strategy would have been the momentum-loser strategy, which would have generated the most negative performance on all employed performance metrics in the 10-year investigated period. The performance of the momentum-loser strategy is on all risk-adjusted measures statistically significant and the results are similar to previous studies investigating momentum-loser portfolios (see for example Jegadeesh & Titman 1993; Chan et al. 1996).

To answer the second research question, the value-momentum combination portfolio P1 outperforms the pureplay investment strategies P3-P6 on all employed performance metrics. However, the results of the momentum-winner P3 and the pure-growth P6 portfolios are non-reliable since the results are statistically insignificant. The ex post Sharpe and modified Sharpe ratios of the value-winner portfolio P1 are substantially larger even when comparing the best performed pureplay portfolio, the pure-value portfolio P5, with the value-winner portfolio P1. The combination portfolio P1 has almost two folds higher ex post Sharpe and modified Sharpe ratios compared to the pure-value portfolio. However, the ex post single factor alpha of the pure-value portfolio P5 are roughly one-third smaller compared to the value-winner portfolio P1. All the risk-adjusted metrics of both portfolio P1 and P5 are statistically significant with a risk level of 1%.

Some noteworthy observations can also be made from the pureplay investment strategies utilized in this study. Since the return of the momentum-loser portfolio P4 is negative, hypothetically it would have been be possible to implement an investment strategy that sells short the momentum-loser portfolio similarly to investment strategies investigated in prior literature (see for example Bird & Casavecchia 2007; Grobys & Huhta-Halkola 2019; Leivo & Pätäri 2011). Furthermore, positive ex post performance of the pure-value portfolio P5 implies that the EBIT/EV valuation multiple could have been successfully employed in a value investing strategy in Nasdaq

Helsinki during the 10-year period. Considering the differences in methodology, the results are corroborative to the results of Pätäri et al. (2016) suggesting that even after 2013, the EBIT/EV single valuation multiple strategy could have yielded excess returns in Nasdaq Helsinki.

It is worth noticing that a more sophisticated asset pricing model could improve the validity of the alpha values and possibly explain what portions of returns could be explained by known stock market anomalies, and even differentiate the proportion of momentum returns from the value-winner portfolio. In the light of the single factor CAPM, the portfolios overperforming the market, including the value-winner portfolio P1, challenge the strong form of the efficient market hypothesis since all returns are not explained by CAPM assuming the hypothetical state of market equilibrium. Due to the inability of CAPM to capture and explain all stock market returns, the results might change in case of implementing more complex asset pricing models. However, the implementation of more sophisticated asset pricing models is left for future research.

The employed risk measures do not capture the risk for a return reversal documented by, for example, Be bondt and Thaler (1985), and Jegadeesh and Titman (1993). To counter the potential of return reversals, some measure for momentum acceleration could be applied to improve risk-adjusted returns and management of investment risk in investment strategies implementing momentum similarly to Bird and Casavecchia (2007), for example. Furthermore, the employed risk evaluation tools employed in this study tell nothing of the potential of a momentum crash in the momentum-loser portfolio P4 documented by Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2016), for example. Momentum crash is not a concern for long-only investment strategies, but in the case a short selling strategy would be implemented to gain excess return from the inferiority of the momentum-loser strategy, a better tool for managing risk should be implemented.

Furthermore, it would be interesting to investigate how much of the portfolio returns stem from the upward trend of the overall market and how the combination portfolio performs in a bearish market environment. Moreover, the low interest rate environment, the exceptionally vast reviving monetary policy, and the increased liquidity in the market could be an interesting factor to consider, when determining the

risk and return of investment strategies. The effect of the latter three are purely speculative thoughts at this point made by the author and may prove to be potential topics for future research. In addition, the use of more complex models could improve risk-adjusted returns, for example, by including an acceleration meter to time the entry into stocks like Bird and Casavecchia (2007).

Momentum, value and combination portfolios are still an intriguing subject in finance research. For example, the EBIT/EV portfolio enhanced with momentum could be investigated in other markets, which could elucidate the effectiveness of the investment strategy in general. Moreover, the inclusion of a larger number of quantile portfolios could provide more information on the combination strategy's performance. The use of 6-month, 9-month or 12-month momentum could also be employed instead of the 3-month momentum in portfolio formation. Another interesting extension for this study would be to investigate the portfolio compositions and explore how many overperforming stocks are allocated to both portfolios similarly to Leivo and Pätäri (2011).

This study has extended the finance literature on the use of EBIT/EV valuation multiple and 3-month momentum in portfolio formation. The value-winner, and the pure-value strategies both could have provided investors with excess returns. However, there is no explicit explanation for the returns from combining value with momentum or why the combination of the strategies outperforms the pureplay strategies. Nor has the academic literature provided a definitive and unanimous explanation for momentum and value investing returns altogether. Therefore, the explanation regarding returns from value, momentum, and value-momentum strategies is still an interesting topic for future research.

REFERENCES

Andrews, D. W. K. (1991) Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica*, 59 (3), pp. 817–858.

Andrews, D. W. K. & Monahan, J. C. (1992) An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator. *Econometrica*, 60 (4), pp. 953–966.

Ardia, D. & Boudt, K. (2015) Testing equality of modified Sharpe ratios. *Finance Research Letters*, pp. 97–104.

Ardia, D. & Boudt, K. (2018) The peer performance ratios of hedge funds. *Journal of Banking and Finance*, pp. 87351–368.

Ardia, D., Boudt, K., (2017) PeerPerformance: luck-corrected peer performance analysis in R. Available: https://cran.r-project.org/web/packages/PeerPerformance/index.html

Asness, C. (1997) The interaction of value and momentum strategies. *Financial Analysts Journal*, 53(2), pp. 29-36.

Balsara, N. & Zheng, L. (2006) Profiting from past winners and losers. *Journal of Asset Management*, 6(5), p. 329.

Barberis, N., Shleifer, A. & Vishny, R. (1998) A model of investor sentiment. *Journal of Financial Economics*, 49(3), pp. 307-343.

Barillas, F. & Shanken, J. (2018) Comparing Asset Pricing Models. *Journal of Finance*, 73(2), pp. 715-754.

Barroso, P. & Santa-Clara, P. (2015) Momentum has its moments. *Journal of Financial Economics*, 116(1), pp. 111-120.

Basu, S. (1983) The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, 12(1), pp. 129-156.

Bird, R. & Casavecchia, L. (2007) Value enhancement using momentum indicators: The European experience. *International Journal of Managerial Finance*, 3(3), pp. 229262.

Bird, R. & Whitaker, J. (2003) The performance of value and momentum investment portfolios: Recent experience in the major European markets. *Journal of Asset Management*, 4(4), p. 221.

Black, F. (1972) Capital Market Equilibrium with Restricted Borrowing. *The Journal of business* (Chicago, Ill.), 45 (3), pp. 444–455.

Bondt, W. F. M. & Thaler, R. (1985) Does the Stock Market Overreact? *Journal of Finance*, 40(3), pp. 793-805.

Bornholt, G., Duo, P. & Malin, M. (2015) Trading Volume and Momentum: The International Evidence. *Multinational Finance Journal*, 19(4), p. 267.

Brandt, M. W., Santa-Clara, P. & Valkanov, R. (2009) Parametric Portfolio Policies: Exploiting Characteristics in the Cross-Section of Equity Returns. *The Review of Financial Studies*, 22(9), pp. 3411-3447.

Brown, S., Yan Du, D., Rhee, S. G. & Zhang, L. (2008) The returns to value and momentum in Asian Markets. Emerging Markets Review, 9(2), pp. 79-88.

Campbell, J., Grossman, S. & Wang, J. (1993) Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics*, 108(4), p. 905.

Carhart, M. M. (1997) On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1), pp. 57-82.

Chan, K. C. (1988) On the Contrarian Investment Strategy. *The Journal of Business*, 61(2), pp. 147-163.

Chan, L. K. C., Jegadeesh, N. & Lakonishok, J. (1996) Momentum Strategies. *Journal of Finance*, 51(5), pp. 1681-1713.

Chen, J. M. (2016) Postmodern Portfolio Theory: Navigating Abnormal Markets and Investor Behavior. New York: Palgrave Macmillan US.

Chen, N. & Zhang, F. (1998) Risk and Return of Value Stocks. *The Journal of Business*, 71(4), pp. 501-535.

Chen, L., Petkova, R. & Zhang, L. (2008) The expected value premium. *Journal of Financial Economics*, 87(2), pp. 269-280.

Conrad, J. S., Hameed, A. & Niden, C. (1994) Volume and Autocovariances in Short-Horizon Individual Security Returns. *Journal of Finance*, 49(4), pp. 1305-1329.

Daniel, K., Hirshleifer, D. & Sun, L. (2017) Short and Long Horizon Behavioral Factors. *NBER Working Paper Series*, p. 24163.

Daniel, K., Hirshleifer, D. & Subrahmanyam, A. (1998) Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, 53(6), pp. 1839-1885.

Daniel, K. & Moskowitz, T. J. (2016) Momentum crashes. *Journal of Financial Economics*, 122(2), pp. 221-247.

Edwards, W., (1968) Conservatism in human information processing. In: Kleinmutz, B. (Ed.), Formal Representation of Human Judgment. John Wiley and Sons, New York, pp. 17—52.

Eling, M. & Schuhmacher, F. (2007) Does the choice of performance measure influence the evaluation of hedge funds? *Journal of Banking and Finance*, 31(9), pp. 2632-2647.

Elton, E., Gruber, M. & Blake, C. (1996) Survivorship bias and mutual fund performance. *Review of Financial Studies*, 9(4), pp. 1097-1120.

Fama, E. & French, K. (1992) The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 47(2), p. 427.

Fama, E. F. & French, K. R. (2004) The Capital Asset Pricing Model: Theory and Evidence. *The Journal of economic perspectives*, 18 (3), pp. 25–46.

Fama, E. F. & French, K. R. (2006) The Value Premium and the CAPM. *Journal of Finance*, 61(5), pp. 2163-2185.

Fama, E. F. & French, K. R. (2012) Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), pp. 457-472.

Fama, E. F. & French, K. R. (2015) A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), pp. 1-22.

Fama, E. F. & French, K. R. (2018) Choosing factors. *Journal of Financial Economics*, 128(2), pp. 234-252.

Fisher, G., Shah, R. & Titman, S. (2016) Combining Value and Momentum. *Journal of Investment Management*: JOIM, 14(2), p. 1.

Gottesman, A., Jacoby, G. & Li, H. (2017) Value investing or investing in illiquidity? The profitability of contrarian investment strategies, revisited. Financial Innovation, 3(1), pp. 1-12.

Gregory-Allen, R., Lu, H. & Stork, P. (2012) Asymmetric extreme tails and prospective utility of momentum returns. Economics Letters, 117(1), pp. 295-297.

Grobys K. & Huhta-Halkola T. (2019) Combining value and momentum: evidence from the Nordic equity market, Applied Economics, 51:26, 2872-2884.

Grundy, B. D. & Martin, J. S. (2001) Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *The Review of Financial Studies*, 14(1), pp. 29-78.

Hong, H. & Stein, J. C. (1999) A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance*, 54(6), pp. 2143-2184.

Hou, K., Xue, C. & Zhang, L. (2015) Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, 28(3), p. 650.

Hou, K., Mo, H., Chen, X. & Zhang, L. (2018) q5. *NBER Working Paper Series*, p. 24709.

Hou, K., Mo, H., Xue, C. & Zhang, L. (2019) Which factors? *Review of Finance*, 23(1), pp. 1-35.

Huang, D., Zhang, H. & Zhou, G. (2017) Twin momentum: Fundamental trends matter. Research Collection Lee Kong Chian School of Business, pp. 1-49

Jarque, C.M. & Bera, A.K. (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economic Letters 6(3), pp. 255–259.

Jegadeesh, N. (1992) Does Market Risk Really Explain the Size Effect? *The Journal of Financial and Quantitative Analysis*, 27(3), pp. 337-351.

Jegadeesh, N. & Titman, S. (1993) Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), pp. 65-91.

Jegadeesh, N. & Titman, S. (2001) Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *Journal of Finance*, 56(2), pp. 699-720.

Lakonishok, J., Shleifer, A. & Vishny, R. W. (1994) Contrarian Investment, Extrapolation, and Risk. *Journal of Finance*, 49(5), pp. 1541-1578.

Ledoit, O. & Wolf, M. (2008) Robust performance hypothesis testing with the Sharpe ratio. *Journal of empirical finance*. 15 (5), pp. 850–859.

Leivo, T. H. & Pätäri, E. J. (2011) Enhancement of value portfolio performance using momentum and the long-short strategy: The Finnish evidence. *Journal of Asset Management*, 11(6), p. 401.

Lintner, J. (1965) The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. The review of economics and statistics, 47 (1), pp. 13–37.

Markowitz, H. (1952) Portfolio selection. *Journal of Finance*, 7(1), pp. 77-91.

Memmel, C. (2003) Performance Hypothesis Testing with the Sharpe Ratio. Finance Letters, 1 pp. 21-23.

Newey, W. K., West, K. D. (1994) Automatic lag selection in covariance matrix estimation. Review of Economic Studies 61, pp. 631–653.

Politis, D. N. & Romano, J. P. (1992) A circular block-resampling procedure for stationary data. In: LePage, R., Billard, L. (Eds.), Exploring the Limits of Bootstrap. John Wiley, New York, pp. 263–270.

Pätäri, E., Karell, V. & Luukka, P. (2016) Can size-, industry-, and leverage-adjustment of valuation ratios benefit the value investor? *International Journal of Business Innovation and Research*, 11(1), pp. 76-109.

Sharpe, W. F. (1966) Mutual Fund Performance. *The Journal of Business*, 39(1), pp. 119-138.

Sharpe, W. (1995) Risk, market sensitivity, and diversification. *Financial Analysts Journal*, 51(1), pp. 84-88.

Tversky, A. & Kahneman, D. (1974) Judgment under uncertainty: heuristics and biases. Science 185, pp. 1124—1131.

Zarowin, P. (1990) Size, Seasonality, and Stock Market Overreaction. *The Journal of Financial and Quantitative Analysis*, 25(1), pp. 113-125.

APPENDICES

APPENDIX 1: PORTFOLIO MONTHLY EXCESS RETURN DESCRIPTIVE STATISTICS

Portfolio	P1	P2	P3	P4	P5	P6	Market
Mean	0.013	0.006	0.009	-0.001	0.011	0.005	0.006
Median	0.015	0.008	0.011	-0.005	0.009	0.003	0.003
Maximum	0.172	0.176	0.195	0.175	0.134	0.135	0.155
Minimum	-0.192	-0.191	-0.219	-0.197	-0.197	-0.206	-0.199
Std. Dev.	0.049	0.05	0.055	0.059	0.051	0.052	0.049
Skewness	-0.491	-0.126	-0.338	0.107	-0.495	-0.374	-0.347
Kurtosis	5.837	5.517	5.478	3.924	5.26	5.102	5.62
Shapiro-Wilk	0.958	0.958	0.97	0.984	0.961	0.957	0.955
p-value	0.001	0.001	0.009	0.159	0.002	0.001	0.001

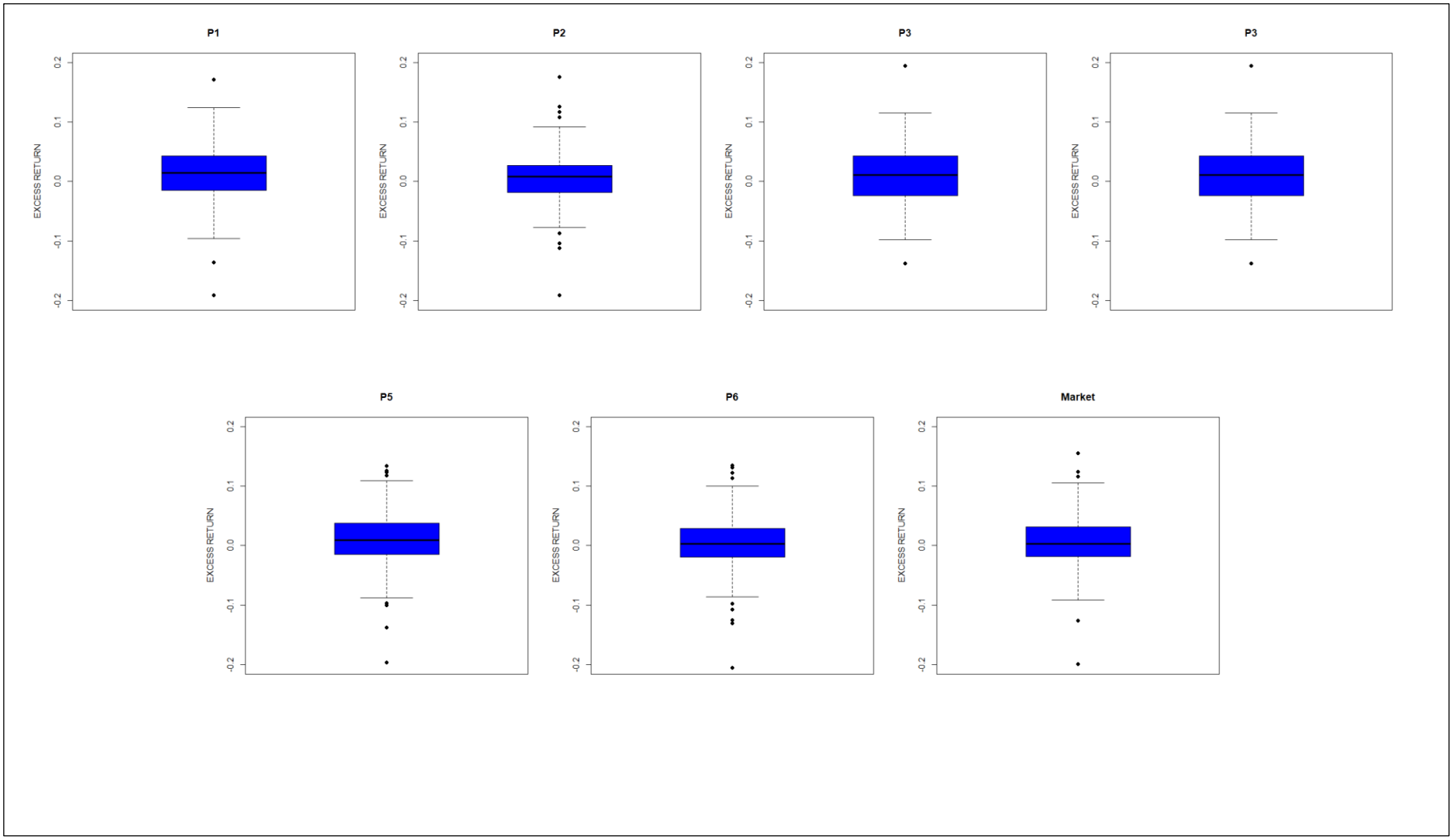
APPENDIX 2: STATISTICAL TESTS ON SINGLE FACTOR ALPHA REGRESSIONS

Portfolio	P1	P2	P3	P4	P5	P6
Jarque-Bera	2.758	0.467	0.247	0.019	1.298	1.283
p-value	0.252	0.792	0.884	0.991	0.523	0.526
Breusch-Pagan	0.711	0.178	2.118	0.581	0.707	4.203
p-value	0.399	0.673	0.146	0.446	0.401	0.04

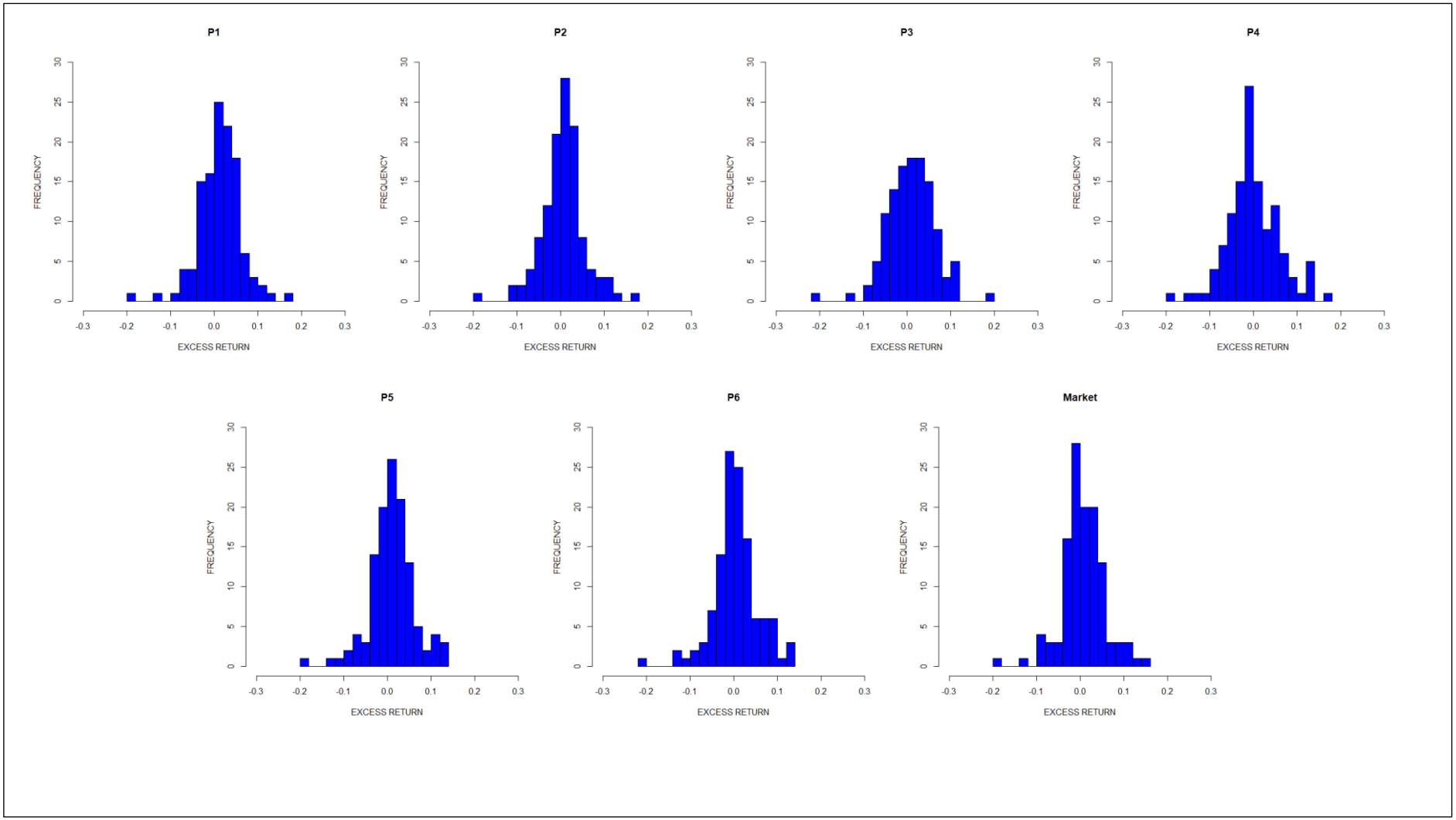
APPENDIX 3: CORRELATION MATRIX ON THE PORTFOLIO EXCESS RETURNS

	P1	P2	P3	P4	P4	P5	Market
P1	1						
P2	0.84	1					
P3	0.91	0.83	1				
P4	0.76	0.89	0.78	1			
P4	0.94	0.85	0.89	0.81	1		
P5	0.84	0.95	0.85	0.85	0.86	1	
Market	0.93	0.94	0.93	0.9	0.94	0.94	1

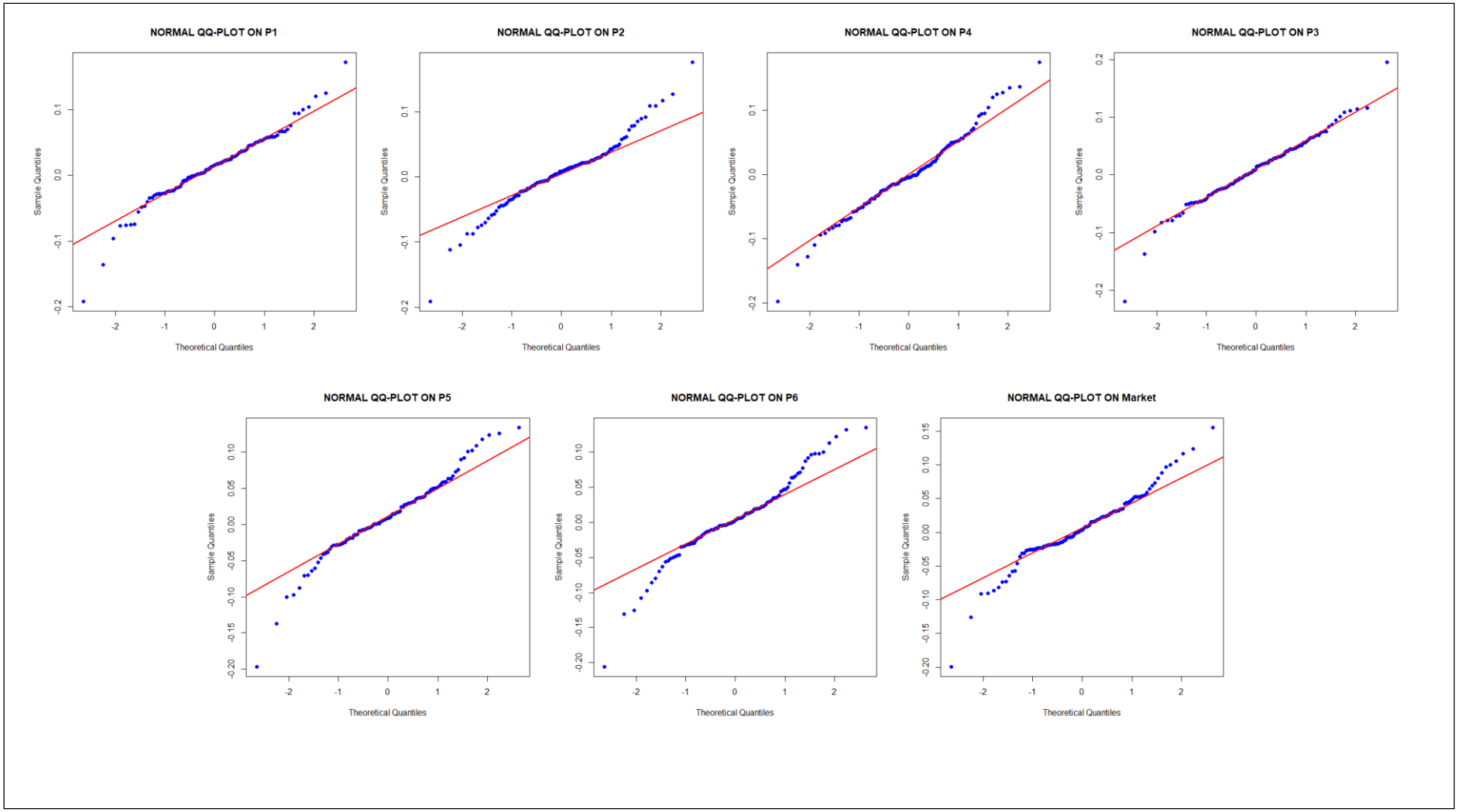
APPENDIX 4: BOXPLOTS ON PORTFOLIO EXCESS RETURNS



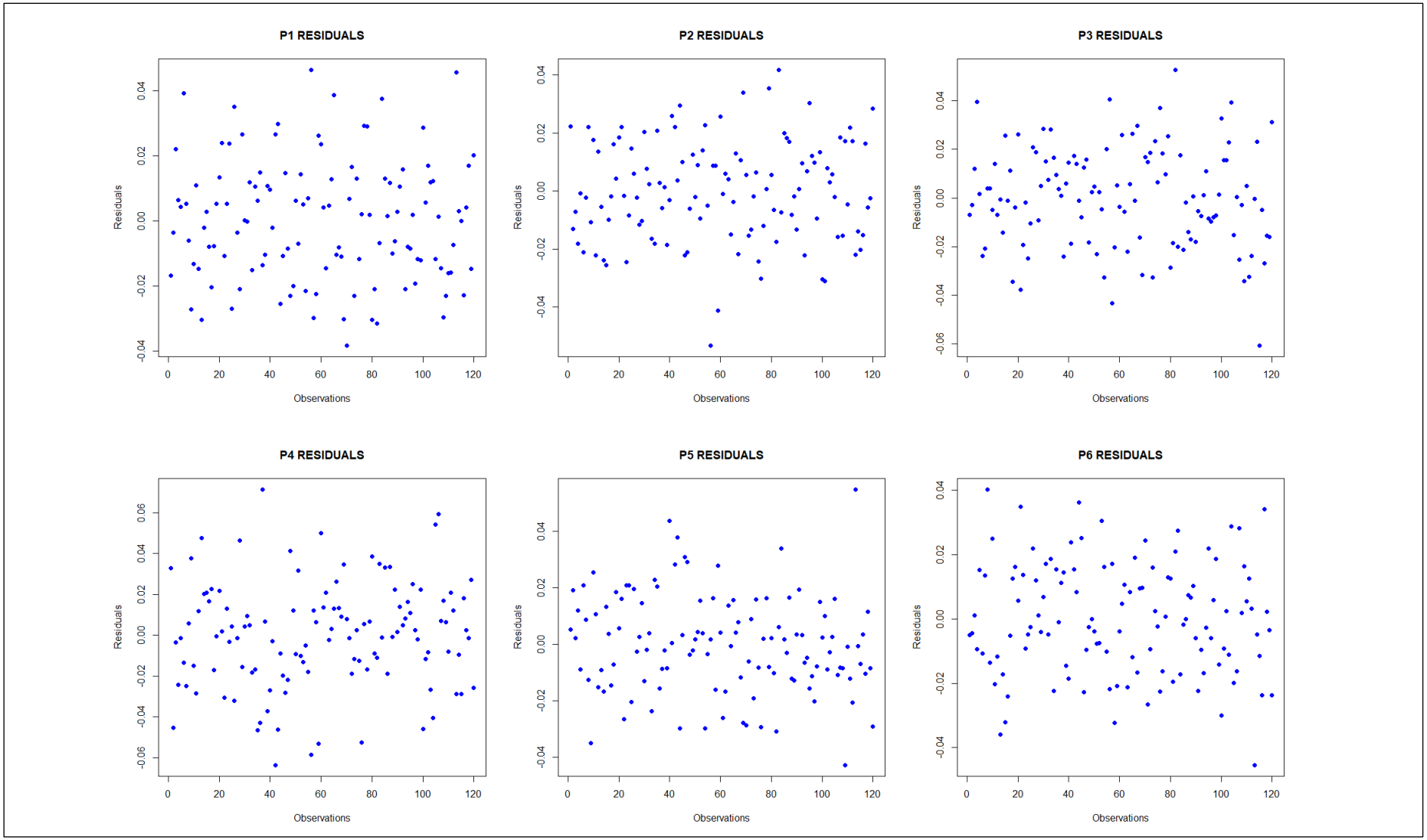
APPENDIX 5: HISTOGRAMS ON PORTFOLIO EXCESS RETURNS



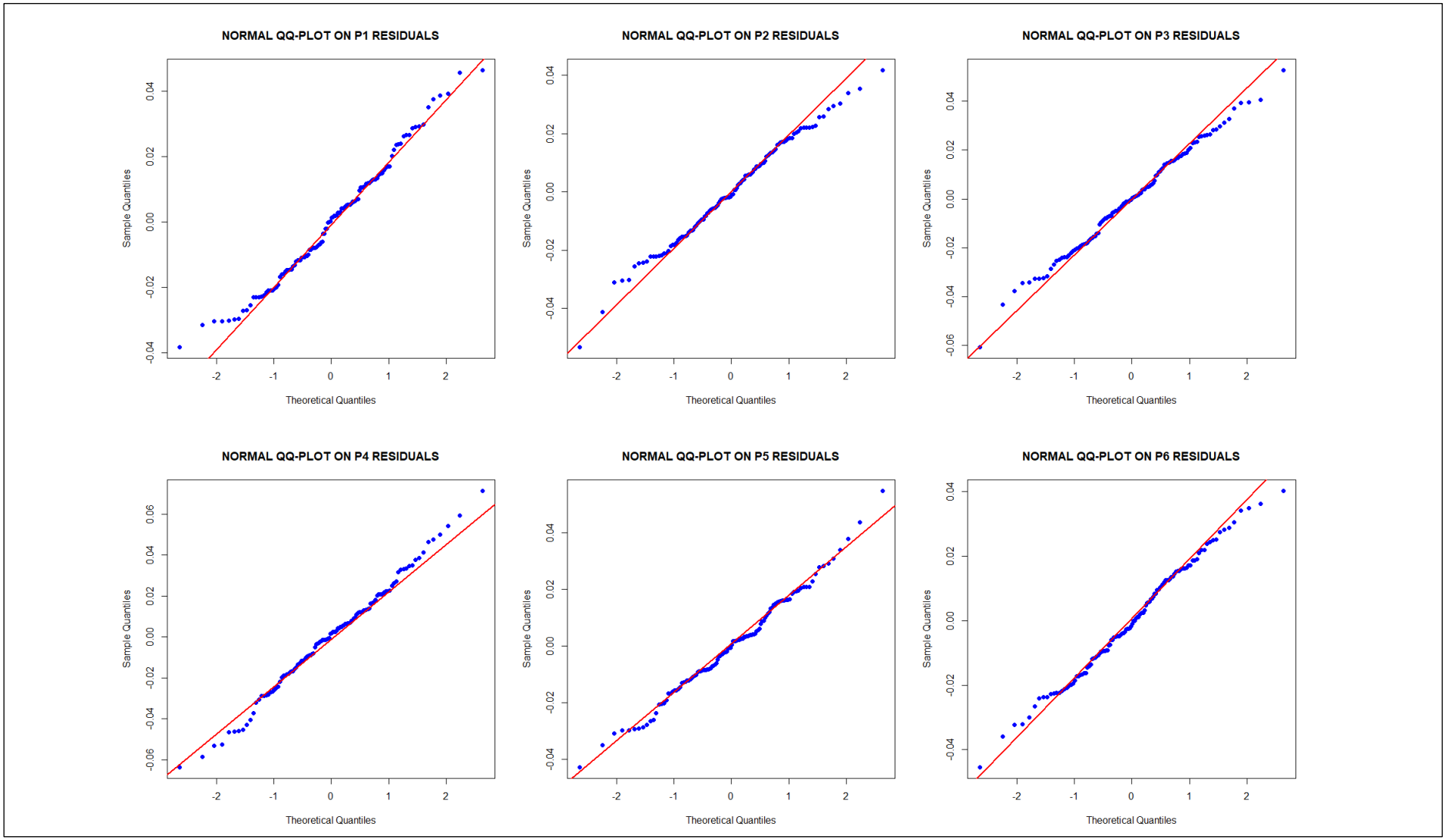
APPENDIX 6: QQ-PLOTS ON PORTFOLIO EXCESS RETURNS



APPENDIX 7: SINGLE FACTOR ALPHA REGRESSION RESIDUAL PLOTS



APPENDIX 8: QQ-PLOTS ON SINGLE FACTOR ALPHA REGRESSION RESIDUALS



APPENDIX 9: CODE FOR THE R

```
#Performance measure calculation and significance testing

# Developed with R 4.0.0
# Author: Dani Porkka 28.08.2020
rm(list=ls())
setwd("~/R")
data<-read.csv("Thesis_data.csv", header=TRUE, sep=";")
str(data)

data$ï..Date<-as.Date(data$ï..Date)
str(data)

names(data)[1]<-"Date"
colnames(data)

#Installing the package by Ardia and Boudt (2020)
#install.packages("PeerPerformance")
library("PeerPerformance")

# Calculating Sharpe and testing significance

SP1<-sharpeTesting(x=data$P1,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))
SP2<-sharpeTesting(x=data$P2,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))
SP3<-sharpeTesting(x=data$P3,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))
SP4<-sharpeTesting(x=data$P4,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))
SP5<-sharpeTesting(x=data$P5,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))
SP6<-sharpeTesting(x=data$P6,y=data$Market, control = list(type=2, hac=FALSE, bBoot=0))

# SP1
SP1_df<-as.data.frame(SP1)
SP1_df$msharpe<-SP1_df[2,2]
SP1_df<-SP1_df[1,]
SP1_dfx<-c(SP1_df[1,2],SP1_df[1,6],SP1_df[1,3],SP1_df[1,4],SP1_df[1,5])
names(SP1_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP1_dfx<-t(SP1_dfx)
SP1_dfx<-as.data.frame(SP1_dfx)

# SP2
```

```
SP2_df<-as.data.frame(SP2)
SP2_df$msharpe<-SP2_df[2,2]
SP2_df<-SP2_df[1,]
SP2_dfx<-c(SP2_df[1,2],SP2_df[1,6],SP2_df[1,3],SP2_df[1,4],SP2_df[1,5])
names(SP2_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP2_dfx<-t(SP2_dfx)
SP2_dfx<-as.data.frame(SP2_dfx)

# SP3
SP3_df<-as.data.frame(SP3)
SP3_df$msharpe<-SP3_df[2,2]
SP3_df<-SP3_df[1,]
SP3_dfx<-c(SP3_df[1,2],SP3_df[1,6],SP3_df[1,3],SP3_df[1,4],SP3_df[1,5])
names(SP3_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP3_dfx<-t(SP3_dfx)
SP3_dfx<-as.data.frame(SP3_dfx)

# SP4
SP4_df<-as.data.frame(SP4)
SP4_df$msharpe<-SP4_df[2,2]
SP4_df<-SP4_df[1,]
SP4_dfx<-c(SP4_df[1,2],SP4_df[1,6],SP4_df[1,3],SP4_df[1,4],SP4_df[1,5])
names(SP4_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP4_dfx<-t(SP4_dfx)
SP4_dfx<-as.data.frame(SP4_dfx)

# SP5
SP5_df<-as.data.frame(SP5)
SP5_df$msharpe<-SP5_df[2,2]
SP5_df<-SP5_df[1,]
SP5_dfx<-c(SP5_df[1,2],SP5_df[1,6],SP5_df[1,3],SP5_df[1,4],SP5_df[1,5])
names(SP5_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP5_dfx<-t(SP5_dfx)
SP5_dfx<-as.data.frame(SP5_dfx)

# SP6
SP6_df<-as.data.frame(SP6)
SP6_df$msharpe<-SP6_df[2,2]
SP6_df<-SP6_df[1,]
SP6_dfx<-c(SP6_df[1,2],SP6_df[1,6],SP6_df[1,3],SP6_df[1,4],SP6_df[1,5])
```

```
names(SP6_dfx)<-c("SR", "SR_M", "DSR", "t-value", "pval")
SP6_dfx<-t(SP6_dfx)
SP6_dfx<-as.data.frame(SP6_dfx)

# Creating a table from the results

tab1<-rbind(SP1_dfx, SP2_dfx, SP3_dfx, SP4_dfx, SP5_dfx, SP6_dfx)
rownames(tab1)<-c("P1", "P2", "P3", "P4", "P5", "P6")
tab1

# Repeating the steps for modified sharpe calculations

MSP1<-msharpeTesting(data$P1,data$Market, control = list(type=2, hac=FALSE, bBoot=0))
MSP2<-msharpeTesting(data$P2,data$Market, control = list(type=2, hac=FALSE, bBoot=0))
MSP3<-msharpeTesting(data$P3,data$Market, control = list(type=2, hac=FALSE, bBoot=0))
MSP4<-msharpeTesting(data$P4,data$Market, control = list(type=2, hac=FALSE, bBoot=0))
MSP5<-msharpeTesting(data$P5,data$Market, control = list(type=2, hac=FALSE, bBoot=0))
MSP6<-msharpeTesting(data$P6,data$Market, control = list(type=2, hac=FALSE, bBoot=0))

# MSP1
MSP1_df<-as.data.frame(MSP1)
MSP1_df$msharpe_M<-MSP1_df[2,2]
MSP1_df<-MSP1_df[1,]
MSP1_dfx<-c(MSP1_df[1,2],MSP1_df[1,6],MSP1_df[1,3],MSP1_df[1,4],MSP1_df[1,5])
names(MSP1_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP1_dfx<-t(MSP1_dfx)
MSP1_dfx<-as.data.frame(MSP1_dfx)

# SP2
MSP2_df<-as.data.frame(MSP2)
MSP2_df$msharpe_M<-MSP2_df[2,2]
MSP2_df<-MSP2_df[1,]
MSP2_dfx<-c(MSP2_df[1,2],MSP2_df[1,6],MSP2_df[1,3],MSP2_df[1,4],MSP2_df[1,5])
names(MSP2_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP2_dfx<-t(MSP2_dfx)
MSP2_dfx<-as.data.frame(MSP2_dfx)

# SP3
MSP3_df<-as.data.frame(MSP3)
MSP3_df$msharpe_M<-MSP3_df[2,2]
```

```
MSP3_df<-MSP3_df[1,]
MSP3_dfx<-c(MSP3_df[1,2],MSP3_df[1,6],MSP3_df[1,3],MSP3_df[1,4],MSP3_df[1,5])
names(MSP3_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP3_dfx<-t(MSP3_dfx)
MSP3_dfx<-as.data.frame(MSP3_dfx)

# SP4
MSP4_df<-as.data.frame(MSP4)
MSP4_df$msharpe_M<-MSP4_df[2,2]
MSP4_df<-MSP4_df[1,]
MSP4_dfx<-c(MSP4_df[1,2],MSP4_df[1,6],MSP4_df[1,3],MSP4_df[1,4],MSP4_df[1,5])
names(MSP4_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP4_dfx<-t(MSP4_dfx)
MSP4_dfx<-as.data.frame(MSP4_dfx)

# SP5
MSP5_df<-as.data.frame(MSP5)
MSP5_df$msharpe_M<-MSP5_df[2,2]
MSP5_df<-MSP5_df[1,]
MSP5_dfx<-c(MSP5_df[1,2],MSP5_df[1,6],MSP5_df[1,3],MSP5_df[1,4],MSP5_df[1,5])
names(MSP5_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP5_dfx<-t(MSP5_dfx)
MSP5_dfx<-as.data.frame(MSP5_dfx)

# SP6
MSP6_df<-as.data.frame(MSP6)
MSP6_df$msharpe_M<-MSP6_df[2,2]
MSP6_df<-MSP6_df[1,]
MSP6_dfx<-c(MSP6_df[1,2],MSP6_df[1,6],MSP6_df[1,3],MSP6_df[1,4],MSP6_df[1,5])
names(MSP6_dfx)<-c("mSR", "mSR_M", "DmSR", "t-value", "pval")
MSP6_dfx<-t(MSP6_dfx)
MSP6_dfx<-as.data.frame(MSP6_dfx)

# Creating a table from the results

tab2<-rbind(MSP1_dfx, MSP2_dfx, MSP3_dfx, MSP4_dfx, MSP5_dfx, MSP6_dfx)
rownames(tab2)<-c("P1", "P2", "P3", "P4", "P5", "P6")
tab2

# JENSEN ALPHA & SIGNIFICANCE TESTING
```

```
#install.packages("Sandwich")
#Install.packages("lmtest")
library("sandwich")
library("lmtest")

#Regressions / Jensen's alfa and beta values
reg_P1<-lm(data$P1 ~ data$Market)
summary(reg_P1)

reg_P2<-lm(data$P2 ~ data$Market)
summary(reg_P2)

reg_P3<-lm(data$P3 ~ data$Market)
summary(reg_P3)

reg_P4<-lm(data$P4 ~ data$Market)
summary(reg_P4)

reg_P5<-lm(data$P5 ~ data$Market)
summary(reg_P5)

reg_P6<-lm(data$P6 ~ data$Market)
summary(reg_P6)

a1<-coef(summary(reg_P1))
a2<-coef(summary(reg_P2))
a3<-coef(summary(reg_P3))
a4<-coef(summary(reg_P4))
a5<-coef(summary(reg_P5))
a6<-coef(summary(reg_P6))

a1<-as.data.frame(a1)
a2<-as.data.frame(a2)
a3<-as.data.frame(a3)
a4<-as.data.frame(a4)
a5<-as.data.frame(a5)
a6<-as.data.frame(a6)

tab3<-rbind(a1,a2,a3,a4,a5,a6)
```

```
rownames(tab3)<-c("Alpha_P1", "Beta_P1", "Alpha_P2", "Beta_P2","Alpha_P3", "Beta_P3","Alpha_P4", "Beta_P4","Alpha_P5", "Beta_P5","Alpha_P6", "Beta_P6")
tab3

#Newey-west standard errors t-test & t-test

b1<-coeftest(reg_P1, NeweyWest(reg_P1))
b2<-coeftest(reg_P2, NeweyWest(reg_P2))
b3<-coeftest(reg_P3, NeweyWest(reg_P3))
b4<-coeftest(reg_P4, NeweyWest(reg_P4))
b5<-coeftest(reg_P5, NeweyWest(reg_P5))
b6<-coeftest(reg_P6, NeweyWest(reg_P6))

tab4<-rbind(b1,b2,b3,b4,b5,b6)

# Summary tables from regressions

c1<-summary(reg_P1)
c2<-summary(reg_P2)
c3<-summary(reg_P3)
c4<-summary(reg_P4)
c5<-summary(reg_P5)
c6<-summary(reg_P6)

tab5<-rbind(c1,c2,c3,c4,c5,c6)

# Testing kurtosis and skewnes

#install.packages("tseries")
library("tseries") #Testing whether the skewness and kurtosis of distributions match a normal distribution

j1<-jarque.bera.test(residuals(reg_P1))
j2<-jarque.bera.test(residuals(reg_P2))
j3<-jarque.bera.test(residuals(reg_P3))
j4<-jarque.bera.test(residuals(reg_P4))
j5<-jarque.bera.test(residuals(reg_P5))
j6<-jarque.bera.test(residuals(reg_P6))

jar_tab1<-c(j1$statistic, j2$statistic, j3$statistic, j4$statistic, j5$statistic, j6$statistic)
```

```
jar_tab_df1<-data.frame(jar_tab1)
rownames(jar_tab_df1)<-c("P1","P2","P3","P4","P5","P6")
colnames(jar_tab_df1)<-"Jarque Bera statistic"

jar_tab2<-c(j1$p.value, j2$p.value, j3$p.value, j4$p.value, j5$p.value, j6$p.value)
jar_tab_df2<-data.frame(jar_tab2)
rownames(jar_tab_df2)<-c("P1","P2","P3","P4","P5","P6")
colnames(jar_tab_df2)<-"Jarque Bera pval"

jar_tab<-cbind(jar_tab_df1, jar_tab_df2)

#Testing heteroskedasticity with Breusch-Pagan

#install.packages("lmtest")
library(lmtest)

bptest(reg_P1)
bptest(reg_P2)
bptest(reg_P3)
bptest(reg_P4)
bptest(reg_P5)
bptest(reg_P6)

bp_tab_1<-c(bptest(reg_P1)$p.value, bptest(reg_P2)$p.value, bptest(reg_P3)$p.value,
bptest(reg_P4)$p.value, bptest(reg_P5)$p.value, bptest(reg_P6)$p.value)
bp_tab_df1<-data.frame(bp_tab_1)
rownames(bp_tab_df1)<-c("P1","P2","P3","P4","P5","P6")
colnames(bp_tab_df1)<-"Breusch-Pagan pval"

bp_tab_2<-c(bptest(reg_P1)$statistic, bptest(reg_P2)$statistic, bptest(reg_P3)$statistic,
bptest(reg_P4)$statistic, bptest(reg_P5)$statistic, bptest(reg_P6)$statistic)
bp_tab_df2<-data.frame(bp_tab_2)
rownames(bp_tab_df2)<-c("P1","P2","P3","P4","P5","P6")
colnames(bp_tab_df2)<-"Breusch-Pagan statistic"

bp_tab<-cbind(bp_tab_df2,bp_tab_df1)

stat_tab<-cbind(jar_tab,bp_tab, swilk_tab, swilk_tab_r) # All statistical tests in one table

# QQPLOT on residuals
```

```
qqnorm(residuals(reg_P1), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P1 RESIDUALS")
qqline(residuals(reg_P1), col = "red", lwd = 2)

qqnorm(residuals(reg_P2), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P2 RESIDUALS")
qqline(residuals(reg_P2), col = "red", lwd = 2)

qqnorm(residuals(reg_P3), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P3 RESIDUALS")
qqline(residuals(reg_P3), col = "red", lwd = 2)

qqnorm(residuals(reg_P4), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P4 RESIDUALS")
qqline(residuals(reg_P4), col = "red", lwd = 2)

qqnorm(residuals(reg_P5), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P5 RESIDUALS")
qqline(residuals(reg_P5), col = "red", lwd = 2)

qqnorm(residuals(reg_P6), pch=16, col='blue', main = "NORMAL QQ-PLOT ON P6 RESIDUALS")
qqline(residuals(reg_P6), col = "red", lwd = 2)

# Plotting residuals

plot(residuals(reg_P1),                    xlab="Observations",ylab="Residuals",main="P1
RESIDUALS",col="blue",pch=16)
plot(residuals(reg_P2),                    xlab="Observations",ylab="Residuals",main="P2
RESIDUALS",col="blue",pch=16)
plot(residuals(reg_P3),                    xlab="Observations",ylab="Residuals",main="P3
RESIDUALS",col="blue",pch=16)
plot(residuals(reg_P4),                    xlab="Observations",ylab="Residuals",main="P4
RESIDUALS",col="blue",pch=16)
plot(residuals(reg_P5),                    xlab="Observations",ylab="Residuals",main="P5
RESIDUALS",col="blue",pch=16)
plot(residuals(reg_P6),                    xlab="Observations",ylab="Residuals",main="P6
RESIDUALS",col="blue",pch=16)

#DESCRIPTIVE DATA-ANALYSIS
any(is.null(data))
any(is.na(data))
#install.packages("moments")
library(moments)
```

```
# Forming a table from the results

sum_stat<-rbind(summary(data$P1), summary(data$P2), summary(data$P3), summary(data$P4),
summary(data$P5), summary(data$P6), summary(data$Market))
row.names(sum_stat)<-c("P1","P2","P3","P4","P5","P6","Market")


sd_tab<-rbind(sd(data$P1) ,sd(data$P2) ,sd(data$P3), sd(data$P4), sd(data$P5), sd(data$P6),
sd(data$Market))
colnames(sd_tab)<-"Standard Deviation"
row.names(sd_tab)<-c("P1","P2","P3","P4","P5","P6","Market")

var_tab<-rbind(var(data$P1) ,var(data$P2) ,var(data$P3), var(data$P4), var(data$P5), var(data$P6),
var(data$Market))
colnames(var_tab)<-"Variation"
row.names(var_tab)<-c("P1","P2","P3","P4","P5","P6","Market")

k_tab<-rbind(kurtosis(data$P1) ,kurtosis(data$P2), kurtosis(data$P3), kurtosis(data$P4),
kurtosis(data$P5), kurtosis(data$P6), kurtosis(data$Market))
colnames(k_tab)<-"Kurtosis"
row.names(k_tab)<-c("P1","P2","P3","P4","P5","P6","Market")

s_tab<-rbind(skewness(data$P1) ,skewness(data$P2), skewness(data$P3), skewness(data$P4),
skewness(data$P5), skewness(data$P6), skewness(data$Market))
colnames(s_tab)<-"Skewness"
row.names(s_tab)<-c("P1","P2","P3","P4","P5","P6","Market")

tab6<-cbind(sum_stat, sd_tab, var_tab, s_tab, k_tab) # Creating a table from the descriptive statistics

# EXPLORATORY DATA-ANALYSIS

# Visualizing the variables with boxplot shows us the mean, median, qvartile values and possible
outliers.
par(mfrow=c(1,1))

boxplot(x=data$P1, pch=16, col='blue', main='P1', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
boxplot(x=data$P2, pch=16, col='blue', main='P2', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
boxplot(x=data$P3, pch=16, col='blue', main='P3', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
boxplot(x=data$P4, pch=16, col='blue', main='P4', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
boxplot(x=data$P5, pch=16, col='blue', main='P5', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
```

```
boxplot(x=data$P6, pch=16, col='blue', main='P6', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")
boxplot(x=data$Market, pch=16, col='blue', main='Market', ylim=c(-0.2,0.2), ylab="EXCESS RETURN")

# Histograms illustrates the normality, skewness and kurtosis of our data variables

hist(data$P1, col='blue', main='P1', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$P2, col='blue', main='P2', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$P3, col='blue', main='P3', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$P4, col='blue', main='P4', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$P5, col='blue', main='P5', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$P6, col='blue', main='P6', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))
hist(data$Market, col='blue', main='Market', xlab='EXCESS RETURN', ylab="FREQUENCY", breaks = 20, xlim = c(-0.3,0.3), ylim = c(0,30))

#QQPLOTS

qqnorm(data$P1, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P1")
qqline(data$P1, col = "red", lwd = 2)

qqnorm(data$P2, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P2")
qqline(data$P2, col = "red", lwd = 2)

qqnorm(data$P3, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P3")
qqline(data$P3, col = "red", lwd = 2)

qqnorm(data$P4, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P4")
qqline(data$P4, col = "red", lwd = 2)

qqnorm(data$P5, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P5")
qqline(data$P5, col = "red", lwd = 2)

qqnorm(data$P6, pch=16, col='blue', main = "NORMAL QQ-PLOT ON P6")
qqline(data$P6, col = "red", lwd = 2)
```

```
qqnorm(data$Market, pch=16, col='blue', main = "NORMAL QQ-PLOT ON Market")
qqline(data$Market, col = "red", lwd = 2)

# Statistically testing normality of return distributions

shapiro.test(data$P1)
shapiro.test(data$P2)
shapiro.test(data$P3)
shapiro.test(data$P4)
shapiro.test(data$P5)
shapiro.test(data$P6)
shapiro.test(data$Market)

swilk_1<-c(shapiro.test(data$P1)$statistic, shapiro.test(data$P2)$statistic,
shapiro.test(data$P3)$statistic, shapiro.test(data$P4)$statistic, shapiro.test(data$P5)$statistic,
shapiro.test(data$P6)$statistic, shapiro.test(data$Market)$statistic)
swilk_1_df<-data.frame(swilk_1)
rownames(swilk_1_df)<-c("P1","P2","P3","P4","P5","P6","Market")
colnames(swilk_1_df)<-"Swilk"

swilk_2<-c(shapiro.test(data$P1)$p.value, shapiro.test(data$P2)$p.value,
shapiro.test(data$P3)$p.value, shapiro.test(data$P4)$p.value, shapiro.test(data$P5)$p.value,
shapiro.test(data$P6)$p.value, shapiro.test(data$Market)$p.value)
swilk_2_df<-data.frame(swilk_2)
rownames(swilk_2_df)<-c("P1","P2","P3","P4","P5","P6", "Market")
colnames(swilk_2_df)<-"Swilk pval"

swilk_tab<-cbind(swilk_1_df, swilk_2_df)

# Saving information into a CSV file

write.csv(tab1,'Sharpe_testing_1.csv', row.names = TRUE)
write.csv(tab2,'Modified_Sharpe_testing_1.csv', row.names = TRUE)
write.csv(tab3,'Alpha_values.csv', row.names = TRUE)
write.csv(tab4,'Alpha_testing.csv', row.names = TRUE)
write.csv(tab5,'Regression_data.csv', row.names = TRUE)
write.csv(tab6,'Descriptive.csv', row.names = TRUE)
write.csv(stat_tab,'Statistical tests.csv', row.names = TRUE)
write.csv(swilk_tab,'Swilk_tests.csv', row.names = TRUE)
```